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Emotion Recognition in Kindergarten Children: Neural Network on Deepface

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Abstract: Emotions are very important to children, and they should be taught how to express themselves properly in order to avoid getting upset. Kindergarten teachers must also be aware of how to manage and understand kids' feelings. Thus, artificial intelligence has an important role in the field of facial recognition, where Convolutional Neural Networks (CNN) are used because of their excellent generalization properties. However, they are complex and do not create accurate results. This work describes a deep face algorithm which is an advanced algorithm used for pre-processing facial images. The emotion reading device was created through the use of Raspberry Pi, using a deep face algorithm to analyze children's facial expressions. This device will analyze and read the child's facial expressions when he enters the kindergarten through a camera in no more than Five seconds. After that, it will display a motivational video that will encourage the child to start a school day full of energy and happiness.

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Keywords: Deepface Emotion analysis, Children, Emotional Facial Expression (EFE), Raspberry Pi, Convolutional Neural Networks (CNN)

1 Introduction

There are many methods that help an individual to express sincere emotions, such as body language and facial expressions, unlike speaking in which the individual might not tell the truth. Nowadays, artificial intelligence has witnessed clear progress in detecting people's emotions either through their facial expressions or through other measurements such as tension, blood pressure, etc. We find that adults can clearly and smoothly express their emotions. On the other hand, children's emotions are quite complex, and they may become frustrated, nervous, sad, jealous, afraid, anxious and angry without knowing how to express such emotions by speaking due to the lack of needed vocabularies. So, how do children express these feelings? The answer is by either playing or reflecting such emotions on their body language, behavior and facial expressions. Children emotions are important, and they should be educated on how to express their emotions especially once they are involved in study environments. Additionally, kindergarten teachers should aware and educate children about managing and expressing their emotions positively and clearly.

The ability to describe children's emotions will help us to understand their emotions and support them if needed. Furthermore, children who under- stand and control their emotions are more likely to speak quietly, express their emotions in appropriate ways, and recover after having difficult emotions such as disappointment and frustration. Also, they can control their heart pulses and act appropriately without hurting themselves or others. This is useful for children because it helps them learn, make friends and be independent. When a child is young, he needs help under- standing his emotions by identifying and naming emotions also knowing how to control emotions.

Through this study, we will understand the emotions of kindergarteners when they come to the kindergarten and manage those emotions by using artificial intelligence. Artificial intelligence has evolved to the extent of mimicking the human mind in understanding human behavior and identifying their emotional states. The idea of the study is to recognize children's emotions by face using DeepFace which is lightweight face recognition and facial attribute analysis in python [1].

In addition, it is an open-source library that includes the most familiar AI facial recognition models, and automatically processes all facial recognition processes in the background. In other words, if you run facial recognition using Deep-Face, you can access real-time facial analysis that includes facial attribute analysis and facial recognition testing with the real-time video feed for your webcam [1]. It works by using the neural net- work and deep learning to identify human faces in digital images to create results that are similar to the performance of human. The system was implemented using Raspberry Pi, which has become used all over the world; especially by engineers and the education sector because of its small size and infinite capabilities in doing what computers do [1]. The used methodology will be taking a photo via Pi Camera then store the image in a folder, after that we will pass the images as an entry into the Deepface algorithm in order to determine the emotion which can be: Angry, scared, happy, sad, neutral, surprised. The results will be sent to a small screen which will be used to manage children's emotions, for example, if the results showed the child is angry, a video will be displayed on the screen that helps him in reducing and controlling the anger emotion also calming him as much as possible. So, this system will significantly help in understanding and managing children's emotions before starting the school day.

2. Related Work

Nowadays, the demand for human-machine inter-action is increasing, and emotion analysis is one of the most important used tools. The tool analyzes emotions through facial expressions which are involuntary facial muscle movements that appear when the individual wants to express emotions [2]. Emotions can be recognized through vocal, text, facial expressions and verbal. Facial expressions have a significant role in determining an individual's emotions and with the development of artificial intelligence, many studies have been published in this field. So, it has been proposed in [3] an intelligent facial emotion recognition sys- tem with real-time facial tracking for a humanoid robot. The system is capable of detecting emotions and facial expressions from images reaching 60 degrees of pose variations. In order to expand the system vision APIs, the public system was integrated with a humanoid robot platform. Additionally, the system is proven its capability to process difficult facial emotion recognition tasks with different pose variations.

Moreover, Gang and Taeho proposed in their work [4] the use of CNN as a base for deep learning. Three different models were submitted to identify success factors that deliver accurate results. Also, different open buildings were used and compared to identify parameters that affect the results. The result of this comparison was satisfactory, but the execution was expensive. A method that recognize real-time facial image emotions was proposed by Kalyani, et al. [5] using different techniques, and implement it in Rasp- berry Pi. The results of this method are accurate by 94%. The work of Patel, et al. [6] reviewed the new machines and deep learning networks that are specifically designed to identify facial expressions based on static images. The summary of this study showed that more research should be con- ducted in this field. While the study of Kim, et al. [7] proposed a real-time streaming image Ping- Pong256 (PP2) algorithm based on Line-Segment Feature Analysis (LFA) and Convolutional Recur- rent Neural Network Model (CRNN) to analyze facial emotions. The suggested method applies the PP2 algorithm to images to encrypt and decrypt them. As a result, the security of the real-time images collected by image devices will be ensured. Also, the performance evaluation ensures the loss rate comparison, and the accuracy level of facial recognition.

In continuation of many studies that have been conducted related to facial expression, Zahara, et al. [8] suggested designing a system that can predict, classify, and identify facial expressions depending on feature extraction by utilizing Open CV library and the Convolution Neural Network (CNN) algorithm. The design is implemented in the Raspberry Pi and includes three processes which are facial feature extraction, facial detection, and emotions classification. The results of predicting facial expressions by using the CNN algorithm were 65.97% accurate. A system analyzing human emotions through facial recognition technology was proposed by Raj, et al. [9] that accurately predicts human emotions. The results' efficiency achieved by this model ranges from 75-80%.

Maafiri, et al. [10] suggested a new facial recognition model using WTPCA-L1 standard for features extraction. The study used WTPCA-L1 algorithm instead of PCA or PCA-L1 to have a better representation of data in a low-dimensional space. The experiment's results showed that the suggested model manages to achieve high recognition performance on three known standard face databases. Also, it is found that suggested model is achieving a better face recognition rate com- paring to the methods related to state-of-the-art. In the [11] study, it proposes CNN-KNN model to improve FER accuracy. So, CNN is used for features extraction while KNN is used for facial expression recognition. The model is trained using fer-2013 data set, and the CNN- KNN hybrid model achieves accurate results by 75.3% and 0.6% structural improvement. A study by Kondaveeti, et al. [12] suggested a Raspberry- Pi that works as a mini-computer including image processing in which it processes and extracts valuable information from images. They selected Raspberry Pi applications that involve image processing. Also, various applications such as image recognition, monitoring, and facial recognition are discussed in the study. The Facial Authentication facial emotions. The suggested method applies the PP2 algorithm to images to encrypt and decrypt them. As a result, the security of the real-time images collected by image devices will be ensured. Also, the performance evaluation ensures the loss rate comparison, and the accuracy level of facial recognition.

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SphereFace2 circumvents the softmax normalization, and the corresponding closed group assumption. Hence, the gap between training and evaluation is bridged effectively, allowing the representations to be enhanced individually by each binary classification task. In addition to designing a specific well-performing loss function. It is demonstrated that SphereFace2 can outperform the state-of-the-art deep face consistently. In the study of Zaho, et al [16], a new facial restoration model has been proposed that enhances the generation and reconstruction. In addition to the model improvement, a new evaluation metric that measures models' ability to keep the identity of the restored faces is introduced. Extensive experiments have proved that the model achieves advanced performance on multiple face restoration benchmarks. Also, the user study shows that the model creates higher quality faces and maintains the identity by 86.4% when comparing it with the best performing baselines.

It was suggested by Yang, et al to create an appropriate integration layer that ensures the features compatibility before integration.[17]. It is noticed that using such a simple approach systematically enhances the recognition of the most difficult face recognition datasets, adding by that a new case on IJB-B, IJB-C and MegaFace. A new deep facial recognition framework datasets is presented by Huang, et al [18] consisting of an embedding matching module, a feature restoration network, and a feature extraction net- work. The feature restoration network uses a two-branch structure based on the convolutional neural network to create a feature image out of the illumination-enhanced image and the primary image. The feature extraction network encrypts the feature image into an embedding that is used by the embedding matching module to verify and identify faces. The overall verification accuracy has been enhanced from 1.1% to 6.7% when tested on the Specs on Faces (SoF) dataset. For facial recognition, the rank-1 recognition accuracy is enhanced by 2.8%.

3 Methodology

3.1 Datasets

LFW:

In 2008, the Labeled Faces in the Wild dataset is created in order to facilitate the facial expression recognition process. This dataset includes 13233 images of 5749 distinctive individuals with images that have highly variable conditions. Therefore, the learned models can be applied to new unseen images [22]. It is noticed that there are many groups that are not well represented within this dataset, for example, a low recording of children and people over 80 years old, a low percentage of women representation, and almost there is no representation of ethnicities.[19]

3.2 Algorithm

DeepFace Network algorithm is based on a Deep Neural Network that has an analytical 3D face modeling based on fiducial points. The network consists of two convolution layers interspaced by a maxpooling layer to ensure that the output of the first convolution layer become more robust for local transactions. Also, the network includes locally connected layers, and the last two layers are connected densely. So, the last two layers are separated by a Dropout layer that works to set the random components of the features to zero. The last layer's output is fed by a k-way SoftMax that creates a distribution over the class labels.[19]

The goal is to develop a time period to recognize the emotions from facial expressions, such emotions can be anger, disgust, happiness, sur- prise and neutrality. So, we used the Deepface library [20], Raspberry Pi II to support us in achieving our goal. It is a MasterCard-sized computer with a System-on-Chip that includes Broad- com BCM2835 and ARM1176JZFS with floating point, running at 900 MHz and a Videocore 4 GPU. The design of the suggested system.

Also, the explanation will be as follows: the real time input photo is captured by the digital camera and fed to the emotions' recognition in form of computer code as an entry. The computer code is entered in the Raspberry Pi II to recognize the emotions, after that it provides a classified emotion as output. Then, the identified emotion is displayed on the screen.

The Processes performed by the computer code fed into the Raspberry Pi II are illustrated in detail in the below.

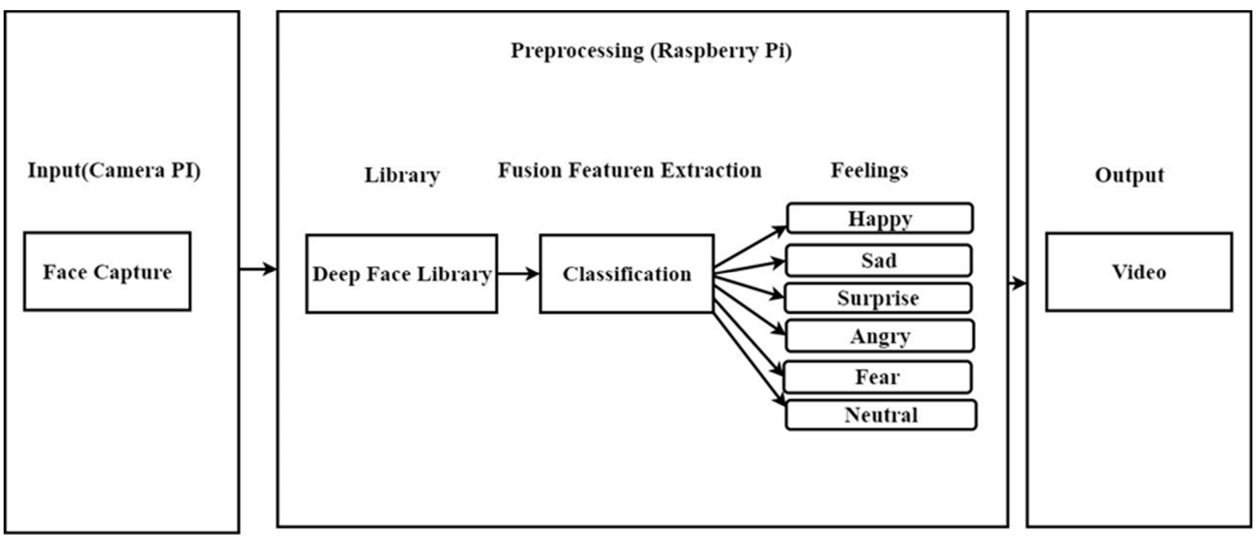

Fig. 1 Real Time Emotion Recognition System.

3.3 Algorithm implementation steps

The following steps explain the used algorithm rule for real-time implementation of the emotion recognition:

- Step 1: the input image is taken using a digital camera.
- Step 2: the image is processed and saved in a folder for easy reading.
- Step 3: features extraction depends on the engineering approach used by the deep face library.

Facial recognition process starts from the human face to identify the needed facial features, expressions and patterns. The human face consists of a basic set of features, such as eyes, nose and mouth. So, the facial recognition technology learns what a face is and what it looks like. This learning process is done by the use of the Deep Neural Network and machine learning algorithms on a set of human faces images that have different angles or positions.[21] Furthermore, it detects the face along with the eyebrows, nose, mouth, etc. Calculate the width of the nose, the distance between the eyes also the shape and size of the nose and mouth. The created model tries to find insights of the face area. Multiple algorithms can be trained to enhance the accuracy of the algorithm to detect faces and positions accurately. In addition, once the face is detected, a further training is con- ducted on the model with the help of computer vision algorithms to detect facial features such as eyebrow angles, eyes gap, nose tip, mouth angles, etc. It is worth to mention that each fea- ture is considered as a nodal point, and each human face has approximately 80 nodal points. So, these features are the key to distinguish and categorize every face in the database.

Fig. 2: hardware.

After features extraction process, these features, facial position and all the basic elements are fed into the model. After that, the model generates a unique feature vector for each face in its digital form. This generated unique code identifies the individual among all the others in the dataset. During the face detection process, the generated feature vector is used to match and search from the database of available faces or entire dataset. The results accuracy is 97.35% on the Labeled Faces in the Wild (LFW) data set, reducing by that the state-of-the-art error by more than 27% and approaching human-level performance.[22] Deepface Algorithm depends on Convolutional Neural Networks (CNN) which is a deep learning algorithm that can take the input image, assign importance (learnable weights and biases) to the different objects in the image, and it is able to distinguish one from the other[10] . The required preprocessing in ConvNet is much lower than other classification algorithms. We find that the facial recognition models in deepface are expect standard-sized inputs and CNN models. Therefore, it is required to resize before the representation process. In order to avoid deformation, deepface adds black padding pixels based on the target size argument after alignment and detection.

Step 4: The emotional state is classified based on the statistical results provided by the algorithm.

Separation of face components:

To separate the components of the face, we use the landmarks of the face in this work. The face landmarks are actually (x, y) that indicate the position of different points of the face.

Face landmarks are used for face positioning and many tasks in face processing. The number of landmarks varies depending on the method used to extract them. The method presented in [27] detects landmarks in three cases of 29, 194, and 68. Figure 3 shows an example of facial landmarks. The components of the face that we intend to separate in this work are the right eye, lift eye, mouth, and nose, with about a 10% margin. The margin is to ensure that the components retain important information.

If fewer components are used, the filters' number that will used in the next step after separating the face components- which using the convolution network - will be reduced. This is because filters of different sizes must be used to identify the features of different areas, such as around the face and chin. In the following, important landmarks in the separation of each component of the face are introduced. Different sizes should be used. In the following, important landmarks in the separation of each component of the face are introduced. Left eye landmarks: To separate the left eye, we will use four land- marks to indicate the length, width, and height of the left eye. These points are as follows: left eye bottom: The left eyes lowest (x, y). left eye left corner: The leftmost (x, y) of the left eye. left eye right corner: The most right (x, y) of the left eye. lefteyetop: The left eyes highest (x, y).

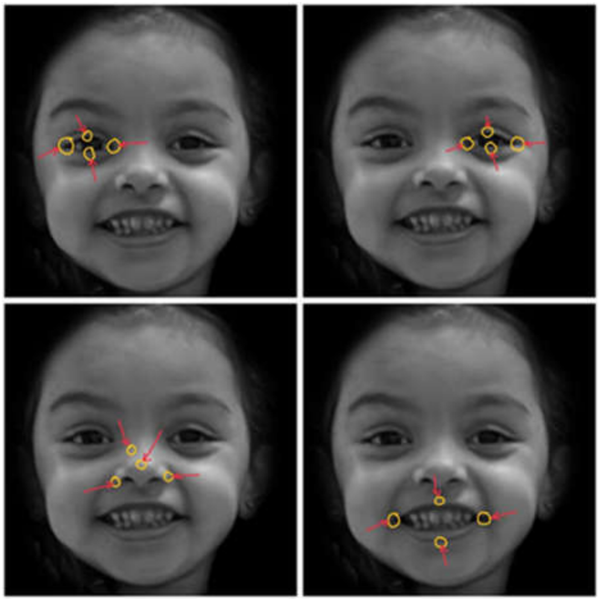

Fig. 3 Important landmarks for extracting face compo- nents.

Different parts of the face in the image can be at different angles, in this case, the distance between the leftmost point (left eye left corner) and the right point of the left eye (left eye right corner) by drawing a vertical line from the left point on the screen and measuring the distance from the right point to it, length of the left eye is obtained.

Also, to obtain the width of the left eye, the distance between the highest point of the left eye (left eye top) and the lowest point of the left eye (left eye bottom) was used. Using the distance plane means using the coordinate distance of two points on only one axis.

Landmarks of the right eye: Measuring the length and width of the right eye is the same as the left eye, except that the leftmost point of the right eye is the inside. The four landmarks used to indicate the right eye's length, width, leftmost point of the nose. Nose tip: as the lowest landmark of the nose (Figure 3).

Mouth landmarks: The last element to be separated is the mouth. The mouth also includes the lower lip and upper lip and can be the largest element of the face. The landmarks used to separate the mouth are as follows: mouth left corner: The mouths leftmost (x, y). Mouth right corner: The most right (x, y) of the mouth. Mouth upper lip top: The highest (x, y) related to the mouth. Mouth lower lip bottom: The mouths lowest (x, y) (Figure 3).

All detached components will be different from their counterparts in the same class. For example, persons eyes can be open, semi-open, and closed. The mouth can be in the state of chewing, laughing, whistling, etc. In addition to this intra-class difference, inter-class differences exist between components. For example, the size of the components can vary, with one person having a long nose and the other wide.

To better understand, the eyes and mouth of a Chinese person can be considered with the eyes and mouth of an Iranian person, how these com- ponents are inherently different between two different people.

Since they are used in the convolutional net- work in the next step after separating the face components, the size of the input images must be the same. These make differences between the classes, and the classes make the input of the convolutional network different in size. There is a noticeable difference in the size of the images. A W window is used for each component to separate to solve this problem. Thus, each face components average length and width are obtained by obtaining the average landmarks. The following is the formula for calculating the average landmarks to separate the components of the face.

Calculating the mean of the leftmost x for the left eye: Since each of the detected landmarks of the face is represented by (x, y), we will use the x of each landmark to determine the left and right points of the various components, and therefore to calculate the left eye, we have a left eye point:

$$LELC = \frac{1}{m}\left(\sum_{i=1}^{M} LELC_{(i,1)}\right) \qquad (1)$$

Where (i, 1) refers to the first element of the element m i. The first element is the x and the second element is the y landmark. Here is the leftmost point of the left eye. LELC is the same as left eye left corner. Calculate the mean of the rightest x for the left eye:

$$LERC = \frac{1}{m}\left(\sum_{i=1}^{M} LERC_{(i,1)}\right) \qquad (2)$$

Where LERC is the same as left eye right cor- ner. Calculate the mean of the highest y for the left eye:

$$LET = \frac{1}{m}\left(\sum_{i=1}^{M} LET_{(i,2)}\right) \qquad (3)$$

Where LET is the same as left eye top. Calculate the mean of the lowest y for the left eye:

$$LEB = \frac{1}{m}\left(\sum_{i=1}^{M} LEB_{(i,2)}\right) \qquad (4)$$

Where LEB is the same as left eye bottom. After finding the average of all points, the length and width of the left eye can be calculated, and the left eye can be separated for all images. The out- put will be a left-eye image with the same length and width for all face images. Displays examples of isolated components of each face. The same is done to separate the other components.

Figure 4. An example of the isolated compo- nents of each face. The output of the separated components is stored in a new matrix called MatOfComponents, which is saved as a file for later use. The new images will be used as a replacement for the original image for the convolution network input.[23]

Step 5:

The results are displayed on a screen. The suitable video will be displayed to the child based on the identified emotional state.

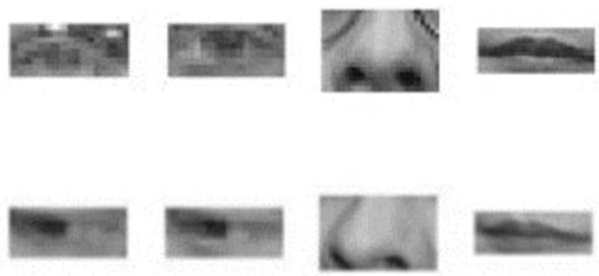

Fig. 4 An example of the isolated components of each face.

Step 6:

The application was done on Raspberry PI device, the package developed for the real- time implementation was tested and deployed in Raspberry Pi II using UNIX operating sys- tem, and there is an external digital camera and screen.

The screen and camera is a module connected to Raspberry Pi II because it does not have a display and input module. In addition, the lap- top can be used as a remote desktop file for viewing and internet input camera in the real- time. So, once an individual clicks the digital camera, his image will be taken and delivered to the Raspberry Pi II. After that, the emotions recognition package can recognize the emotions and display on the screen the suitable video.

4 Results and Discussion

Facial recognition process starts from the human face to identify the needed facial features, expressions and patterns. The human face consists of a basic set of features, such as nose, eyes, and mouth. So, the facial recognition technology learns what a face is and what it looks like. This learning process is done by the use of the Deep Neural Net- work and machine learning algorithms on a set of human faces images that have different emotions. The following are the steps that support facial emotion recognition.

- Face Detection: this step is the main one, in which the face will be detected along with its features and dimension.
- Facial alignment: this step involves normalization of the detected face to speed up training. Experiments indicate that facial alignment has increased facial recognition accuracy by about 1%.
- Feature Extraction: local features are extracted out of the image with the help of algorithms.
- Facial Recognition: this is the last step which includes matching the input face with images in the data set to identify facial emotions

To determine the accuracy of our proposed sys- tem in the real time, classification results were recorded for six basic expressions which are: angry, scared, happy, sad, neutral, surprised. So, we tested 30 children who performed 3 expressions by looking at a webcam that linked to Raspberry Pi as shown in the figure.

Implementing real-time emotion recognition in Raspberry Pi might be a new technology, and can be utilized in different applications due to its lightweight and consumes less energy.

DeepFace correctly predicted 88/90 photos, achieving 88.89% accuracy.

Table 1: Comparing the results of previous studies with the current study

Algorithm	Accuracy
Deepface	97%
CNN	97%
CNN-KNN	75.3%
(CNN) algorithm and OprnCV library	69.97%

Three of the results were shown for different cases of emotion: happy and angry, and the experiment was conducted for an adult and a child to verify the validity of the result, we found as evident in the images; The sample feelings were correctly read 100%, making the system ready for actual application.

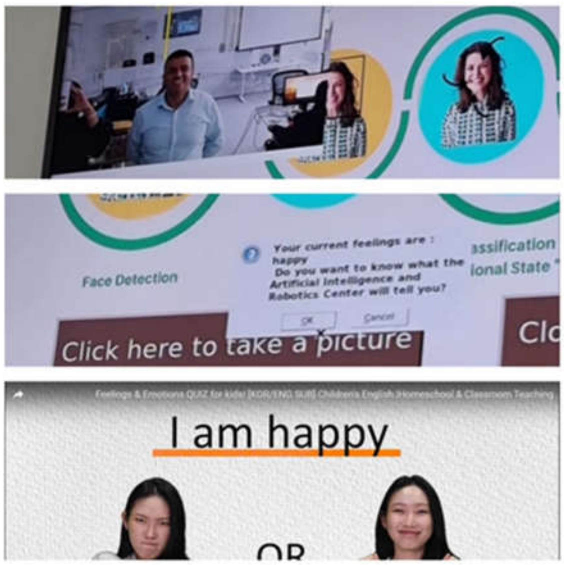

Fig. 5: The result of the happy state test on an adult, and the result represented happy, which is 100% correct.

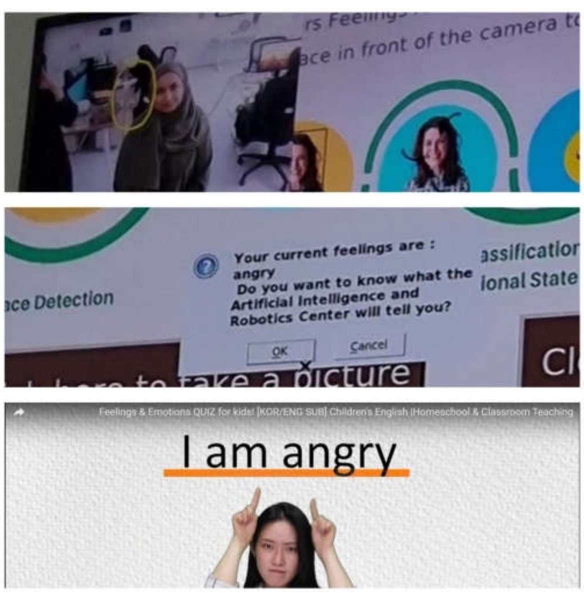

Fig. 6: The result of an anger test on an adult, and the result was 100% correct.

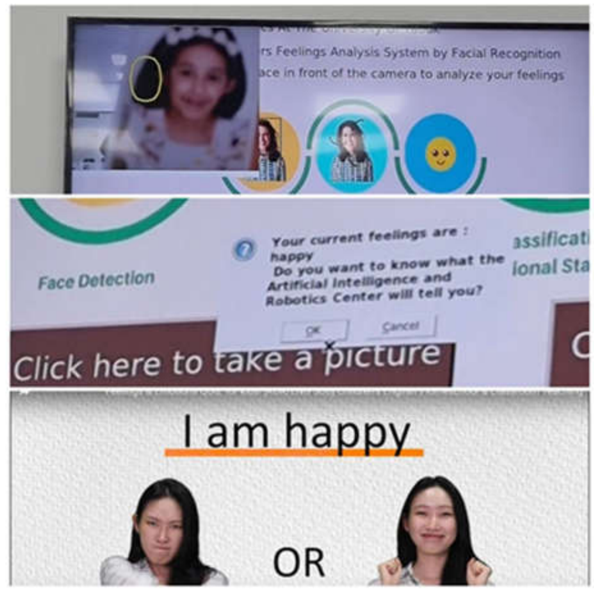

Fig. 7: The result of a happy condition test on a child, and the result was 100% correct.

5 Conclusion

This study tries to build a model to know the analysis of children's aspects in the kindergarten using the DeepFcae algorithm, and this library was relied on instead of CNN because it is a lot of error algorithm and we find that previous studies prove that they are complicated in dealing, this research only uses educational bodies as research object. Through the experimental analysis, the research conclusions are a summary of the possi- bility of analyzing the features of the child's face by taking a picture and then classifying it accord- ing to the classifications included in the Deepage algorithm, which are six works: sadness, joy, anger, fear, surprise, and finally the natural state, then a motivational video is displayed In order to man- age the feelings of the child, in future research, you must circumvent the study of the feelings of the child through the entire body language and mea- sure the heartbeat to conclude stronger accuracy than the current.

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