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3 Facial Expression Recognition Using Neural Network

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ABSTRACT

Human emotions are states of mental health that resolve spontaneously rather than through conscious exertion, and are accompanied by physiological changes in the facial muscles that signify expressions. Nonverbal communication methods such as expressions, eye movements, and gestures are used in many applications of human-computer interaction. Identifying emotions is not an easy task because there is no difference between the emotions of a face, and there is also a lot of complexity and variability. The machine learning algorithm uses some open features to model the face. In this work, convolutional neural networks (CNNs) were developed to identify the expression of facial emotions. Facial expressions play an important role in the nonverbal communication that takes place in a person's inner emotions that are reflected on his or her face.This work has been used the Viola-Jones algorithm to detect the eye and lips region from a face and then with the help of the neural network. Also, Machine Learning techniques, Deep Learning models, and Neural Network algorithms are used for emotion recognition. This work will be proposed as an effective way to detect anger, contempt, disgust, fear, happiness, sadness, and surprise.

Keywords: Emotion Recognition, Emotions, Feature Extraction, Neural Network, Viola-Jones

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1. INTRODUCTION

Facial expressions play a key role in understanding and recognizing emotions. Even the term “interface” suggests the importance of the face in communication between two entities. Studies have shown that reading facial expressions can dramatically alter the interpretation of what is being said and control the flow of conversation. A person's ability to interpret their emotions is very important for effective communication. The proportion of up to 93% of communication used in a normal conversation depends on the emotion of an entity. For ideal human-machine interfaces (HCI), it would be desirable for machines to be able to read human emotions. This research focuses on how computers can correctly detect the emotions of their various sensors. This experience was used as a face image as a means of reading human emotions. Research on human emotions dates back to Darwin's pioneering work and has since attracted many researchers to the field. Seven basic emotions are universal for humans. Namely, neutral, angry, disgusted, fearful, happy, sad and surprised, and these basic emotions can be identified from a person's facial expression. This study suggests an effective way to identify these four emotions using the neutral, happy, sad and surprising frontal facial emotions. Various methods of recognizing emotions have been proposed in recent decades. Many algorithms have been proposed to develop system applications capable of very well detecting emotions. Computer applications could communicate better by altering reactions in various interactions depending on the emotional state of human users. A person's emotions can be determined by the tongue, face, or even gesture. The work presented in this article examines the recognition of facial expressions.

For facial emotion recognition, the traditional approaches usually consider a face image that is distinguished from an information picture, and facial segments or milestones are recognized from the face districts. After that, different spatial and worldly highlights are separated from these facial segments. At last dependent on the separated highlights a classifier, for example, Keras library, random forest, is trained to produce recognitions results. This work is an applied, deep learning model. Deep learning is a well-set model in the pattern recognition domain. It uses a Convolutional Neural Network (CNN) algorithm using Keras library. CNN is a specific sort of artificial neural network that uses a machine-learning unit. CNN applies to objects detections, face recognition, image processing, etc. Deep convolutional neural network (DCNN) composition of many neural network layers. Which is also can be able to extract significant features from the data.

2. LITERATURE REVIEW

In a research field of emotion detection, there is a contribution of several domains like machine learning, natural language, neuroscience, etc. In previous works, they individually rummaged facial expressions, voice features, and textual data as universal indicators of emotions. Emotion can be classified into several static classifications like happiness, sadness, disgust, anger, fear, and surprise. In later works are improved by combining the image, voice, and textual data. The fusion of this data gives the maximum accurate result. This type of fusion can be done in three ways early, late, or hybrid. Other ethos features the elements of emotion and the collaborations between emotional processes and other intellectual procedures.

2.1. Emotion Detections Through Facial Feature Recognition [5]

This work deals with the emotion recognition with the Machine learning using support vector machine (SVM). Some principles are work to detection, extraction, and evaluation of facial expressions of image. These are:
i) Viola-Jones cascade object detectors and Harris Corner key points to extract faces and facial features from images.
ii) Histogram Of Oriented Gradient (H OG) Feature Extraction.
iii) Support vector machines (SVM) to train a multi-class predictor to classify the seven basic human facial expressions such as: (anger, contempt, disgust, fear, happiness, sadness, surprise).

Computers can easily recognize facial expressions and discover a person's motive, including entertainment, social media, content analysis, criminal justice, and healthcare. Here we mainly discuss two approaches such as: (Zhang approach and Gabor wavelet coefficients). Zhang has shown that a lower resolution (64x64) is sufficient. We're going to change the size of the extracted areas to 100x100 pixels.
If this use only the HOG and SVM classifier, the detection accuracy is 81%, which is much better than that of a fisherman. Only approach. When using the double classifier method, the accuracy is only 81% that of HOG, but the testing process is 20% faster.

2.2. SVM Point-based Real-time Emotion Detection [2]

This thesis deals with the detection of emotions in machine learning using a cascade of a multi-class support vector machine (SVM) and a binary SVM. This algorithm is designed to extract emotions based on the movement of 19 characteristic points. These characteristic points are located in different areas of the face such as the mouth, eyes, eyebrows and nose. He mainly works on rigid, unchangeable points in the nose. Its division into face recognition and action unit (AU). Computers can easily recognize facial expressions and discover a person's subject, including entertainment, social media, content analysis, criminal justice, and healthcare.

One final suggestion for improvement is the fact that the user in the real-time app should keep the same distance from the camera from which the neutral frame was captured. Otherwise the theory behind the displacement reports is no longer valid. Rescaling neutral distances based on user movements can be a solution to this problem.

3. RESEARCH METHODOLOGY

This work considers the leading challenge faced by machine learning and the entire system is the training part. Where the system has to train by using real data of human face reactions. For example, if the system has to detect an angry face then the first system has to be acquainted with the angry face. Also if the system has to detect a happy face then the first system has to be acquainted with the happy face. To antecedents the system with this emotion types, the re-training process has been used. The re-training data were collected from the real world. The hardest part of this system was the re-training part. There are also many other parts of the system. Machine learning is a strong tool that enables data analysis of large databases more proficiently and fleetly. This enables the capability of detection emotion more accurate. It gives feedback in real-time. The system did not wait for the result for the future, not the image has to be stored. With help of modern-day computers, neoteric data mining techniques can analyze thousands of data within a very short amount of time saving lots of hours. Besides, using and installing such programs costs significantly less. If properly optimized these data mining techniques can give perfect outcomes than a human. This work resented a general and feasible framework for emotion data mining to identify emotion patterns using machine learning. This chapter proposed the program based on the Deep learning model and computer vision emotion recognition. This proposed method uses the CNN algorithm for this chapter. This proposed a more advanced method than the one that recognized only seven emotions with CNN. Their emotion recognition method using deep learning followed four steps, as follows.

(1) Public face database training with CNN

(2) Extract seven probabilities for each face frame.

(3) Aggregation of frame probabilities into fixed length image descriptors for each image in the data set.

(4) Classification of all images using a support vector machine (SVM) trained on image descriptors from the competition training set.

3.1 Emotion Database

In the data collection steps, this is used both in real-world media and online media to collect as much data as that could. Real-world includes different types of emotional pictures of friends and family members, relatives, some known unknown people's different kinds of facial expressions. They culled data was initially stored for future analysis. From online media, the data is collected data set from kaggle.com. This site uploaded this data set 6years ago. This site most trusted data set of emotions. This converted the data into 48×48 pixel grayscale images of faces. It contains two sections pixels and feelings. The feeling section contains a numeric code which runs from 0 to 6 in figure 1. What's more, the pixel section contains a string incorporated in statements for each picture. Furthermore, the picture should be only the picture of a face. So the collected pictures are resized and cropped picture of a face.

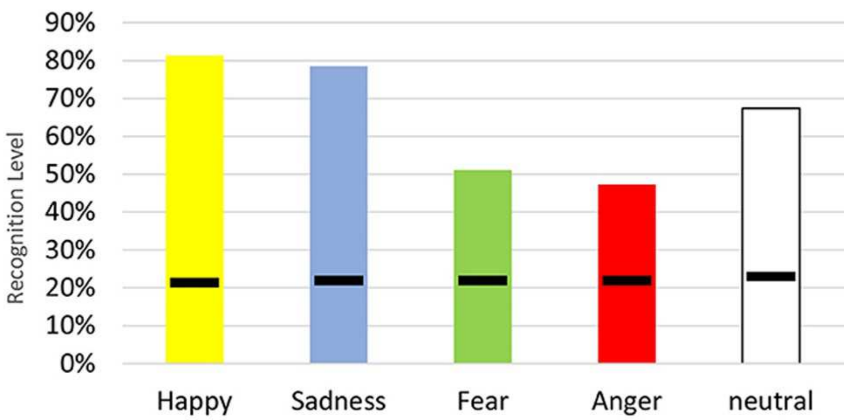


Fig. 1. Level of Emotion

3.2 Training phase using deep learning

A great way to use deep learning to categorize images is to create a convolutional neural network (CNN). The Keras library in Python makes it easy to create a CNN. Computers display images with pixels. Pixels in images are usually related. For example, in figure 2, a particular group of pixels may represent an edge in an image or other pattern. Convolutions use it to identify images. A convolution multiplies a pixel matrix with a filter matrix or a "kernel" and sums the multiplication values. Then the convolution slides to the next pixel and repeats the same process until all pixels in the image are covered. This process is shown below.

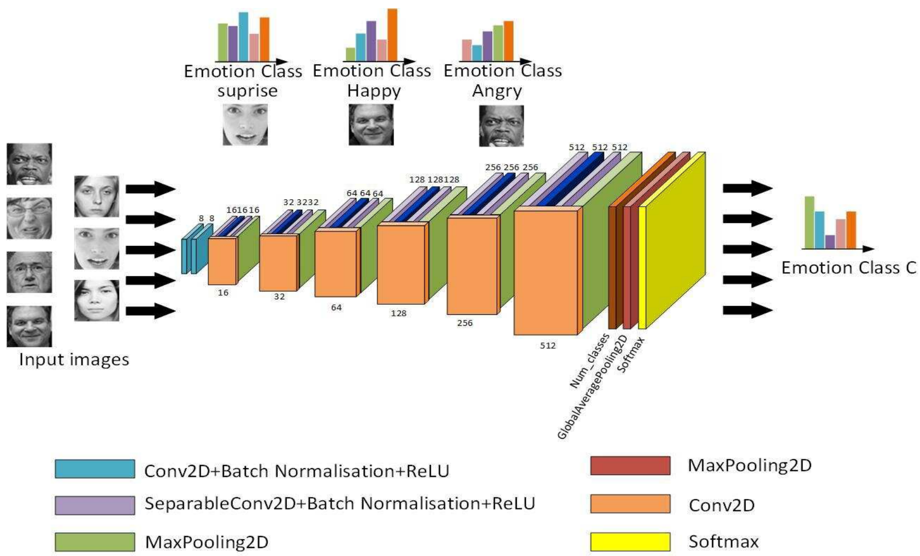


Fig. 2. Emotion detection using Convolutional Neural Network

The type of model we are going to use is Sequential. Sequential is the easiest way to create a template in Keras. You can create a model layer by layer. We use the "add ()" function to add layers to our model. Our first 2 layers are Conv2D layers. These are convolutional layers that process our input images, which are considered two-dimensional matrices. 64 in the first layer and 32 in the second layer are the number of nodes in each layer. This number can be higher or lower depending on the size of the dataset. In our case, 64 and 32 are working fine, so we'll stick with that for now. The kernel size is the size of the filter matrix for our convolution. So a kernel size of 3 means we have a 3x3 filter matrix. You will find a reminder on this subject in the introduction and in the first photo. Activation is that function. The activation function that we use for our first two layers is the ReLU, or rectified linear activation. It has been shown that this activation function works well in neural networks. Our first shift also has a registration form. This is the shape of each input image, 28,28,1 as seen earlier, where 1 means the images are in grayscale. There is a “flatten” layer between the Conv2D layers and the dense layer. Flattening acts as a link between folding and dense layers. The model will then make its prediction based on the most likely option. Then you need to compile this template. Compiling the model requires three parameters: optimizer, loss, and metrics. The optimizer controls the learning rate. It will use "Adam" as an optimizer. Adam is a good optimizer in many cases. The Adam Optimizer adjusts the learning rate during training. The learning rate determines how quickly the optimal weights for the model are calculated. A slower learning rate can result in more accurate weights (up to a point), but the time required to calculate the weights is longer. We will use a "categorical cross-entropy" for our loss function. This is the most common classification option. A lower score indicates that the model is performing better. To make interpretation even easier, the "Precision" metric is used to display the precision score on the validation set while training the model. To train, he uses the "fit ()" function for his model with the following parameters: training data (train_X), target data (train_y), validation data and number of epochs. The test set supplied with the data record is used for the validation data and is divided into X_test and y_test. The number of epochs indicates how often the model scans the data. The more eras we run, the better the model gets up to a point. After this point, the model stops improving with each epoch. For our model we set the number of epochs to 3. After 3 epochs, it achieved an accuracy of 93% for this validation set.

3.3 Detection

K-means clustering was used with the number of clusters assumed to be two. Here, the maximum value is determined in all rows and its average is determined. Likewise, the minimum value is found in all rows and its average is determined. Using these two points as a basis, pixel values closer to the maximum average are grouped into one cluster, and pixel values closer to the minimum average are grouped into another cluster. Based on the result of clustering, the total number of components in the image is calculated. Based on the number of components, the person's eyes are first segmented using the bounding box feature. Because the eye or eyebrow forms the first element when pixel values are passed in columns, the eyes are segmented first. Using the ocular matrix, other parts of the face are segmented using a distance-based algorithm. The resulting image after running k means grouping for different expressions are shown in figure 3.

Fig. 3. K-means clustering segmentation outputs

The Viola Jones algorithm is a widely used mechanism for object recognition. The main characteristic of this algorithm is that training is slow but detection is fast. This algorithm uses the basic hair function. Hair features are the relevant features for face recognition.There are various types of features such as:

Fig. 4. Edge Features

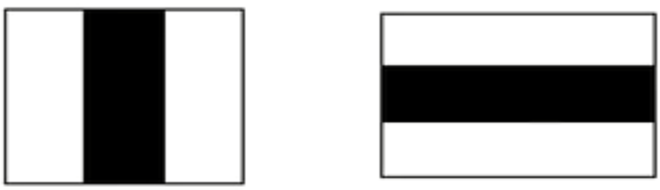


Fig. 5. Line Features

Fig. 6. Four Rectangle Features

For example, we need face detection of a person then we need at first image conversion in grayscale then second step image segmentation.

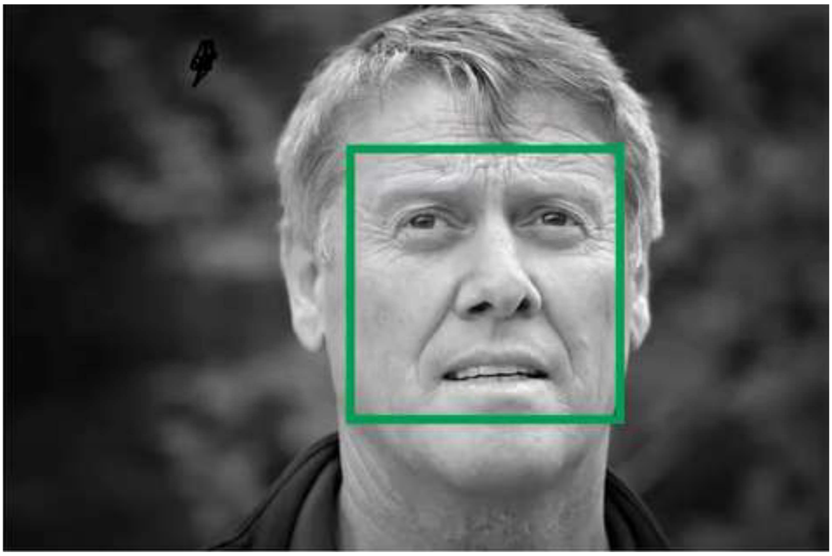


Fig. 7. Landmark image

Suppose we need to detect the eyebrow. Then we need edge features. If we want to detect nose then we need line features black-white-black in figure 7. If we want to detect teeth then we need edge features. After using these Haar features the image goes on the next feature. The ratio between these detected features is used in emotion detection.

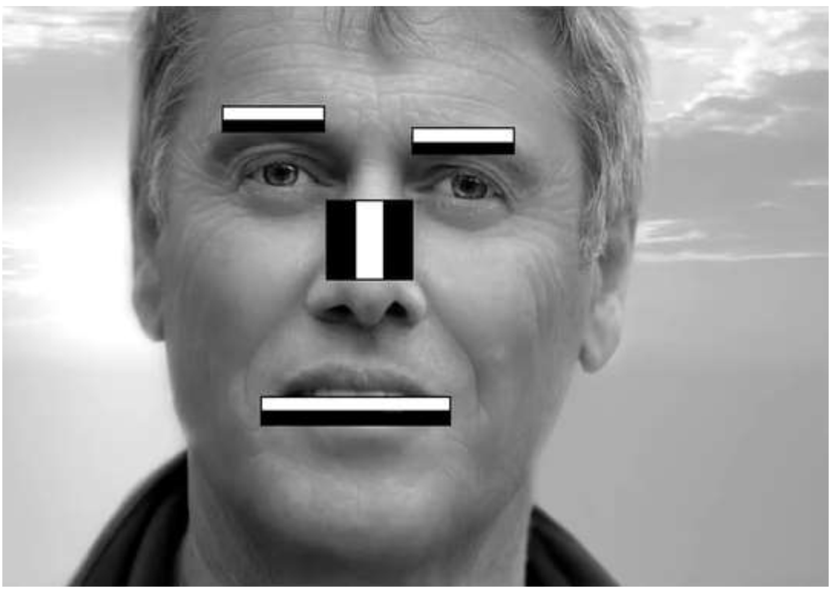


Fig. 8. Haar features image

We can calculate value by using Fourier equation,

$$\Delta = dark - white = \frac{1}{n}\sum_{black}^{n}[(x) - \frac{1}{n}\sum_{white}^{n}](x)$$

For ideal Haar features in figure 8,
The black region value is 1 and the white region value is 0. So the difference between dark and white 1-0=1.
Δ for ideal Haar features is 1
For real image,
If we calculate the black region and we average it's when we get 0.74 and the same way white region value is 0.18. So the difference between dark and white: 0.74-0.18=0.56
Δ for real image: 0.56.

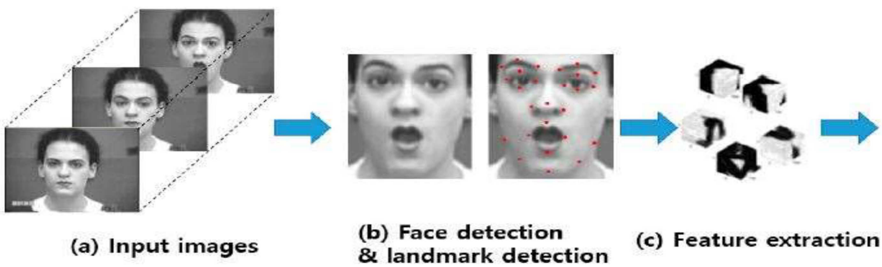


Fig. 9. Feature extraction

Neural networks are generally organized in layers. Layers consist of several interconnected nodes containing an activation function. The models are presented to the network through the input layer, which communicates with one or more hidden layers, where the actual processing is done through a weighted link system. This facial expression recognition system process is divided into three phases: image preprocessing, which includes recognition of the face and parts of the face using the Viola-Jones algorithm, extraction in Figure 9 facial features and classification of features using CNN.
Keras is an open source neural network in Python used for preprocessing, modeling, evaluation, and optimization. It is used for high level APIs because it is processed by the backend. It is designed to create a model with a loss and optimization function and a learning process with an adaptation function. For the backend, it was developed for low level convolution and computation under tensors or Tensor Flow. Importing the following Python libraries is used for preprocessing, modeling, tuning, testing, and displaying emotions with a maximum percentage. It uses sequential model and some layers like image

preprocessing, convolutional layer, pooling layer, flattening and dense layers, activation, ReLU. Image preprocessing is the first phase of the proposed system and includes facial recognition and FPs detection and extraction. It uses the Viola Jones facial recognition framework, a robust algorithm that allows images to be processed extremely quickly in real-time situations. This algorithm detects the facial area regardless of the variance in size, background, brightness and spatial transformation of the raw input image. Face FP recognition is achieved by combining classifiers in a cascade structure, which can increase recognition performance while reducing computational complexity. The final classifier is calculated by the linear combination of all weak classifiers, separating the positive and negative values in terms of weighted error (each learner's weight is directly proportional to their accuracy).

The face is first recognized, cropped, extracted and normalized to a size of 64 x 64 pixels. Then the parts of the face (eyes and mouth) are recognized, cropped and extracted from the normalized face image. The extracted face parts will be resized to the same size of 32 x 64 pixels. The reduced image scale reduces the information that must be learned from the network and speeds up training faster and with less storage costs. Convolutional layers are added to provide greater precision for large amounts of data. The data set is collected from a CSV file (in pixel format) and converted into images. Then the emotions are classified with the appropriate expressions. Here, the emotions are classified as happy, sad, angry, surprised, neutral, disgusted and afraid with 34,488 images for the training data set and 1,250 for the tests.

Each emotion is expressed in different facial features such as eyebrows, open mouth, raised cheeks, wrinkles around the nose, wide open eyelids and much more. Train the large data set for better accuracy and a result that is the feature class for an input image. Pooling is a concept of visual recognition of deep learning objects that is associated with convolution. The idea is that a convolution (or a local neural network detector) maps an area of an image onto a feature map. For example, a 5 × 5 array of pixels could be mapped onto oriented edge features. Flattening occurs when you flatten all of the Photoshop layers into a single background layer. Layers can increase the file size and thus tie up valuable processing resources.

To reduce the file size, you can merge some layers or even reduce the whole image to one background layer. The dense layer is the deeply connected regular neural network layer. This is the most commonly used layer. The dense layer performs the following operation on the input and returns the output. Based on the connecting forces (weight), blocking or excitation and transfer functions, the activation value is transferred from node to node. Each of the nodes adds up the received activation values. Then the value is changed according to its transfer function. In Keras, the task can be implemented in our network architecture by adding exclusion layers. Each suppression level removes a custom hyperparameter of units from the previous level on each stack. Remember that in Keras the entry level is assumed as the first level and is not appended with add. ReLU is one of the most popular types of non-linearity in neural networks that are applied after the convolution layer and before maximum pooling. It replaces all negative pixel values on the feature map with zero. It is usually used after the fold layer.

Example: ReLU is the max (x, 0) function with input x, matrix of a folded image. ReLU then sets all negative values in the x matrix to zero and all other values are held constant. ReLU is calculated after convolution and is therefore a nonlinear activation function like als or sigmoid. Adam is an optimization algorithm that can be used in place of the classic stochastic gradient descent method to iteratively update lattice weights based on training data. It has been found that there are many endeavors have been taken using several automated techniques to analyze emotions. However, most of them are found without any establishing framework and describing how to properly use them. More specifically, understanding and maintaining the emotion analysis capability can help law-enforcement authorities effectively use machine learning techniques to track and identify emotion patterns.

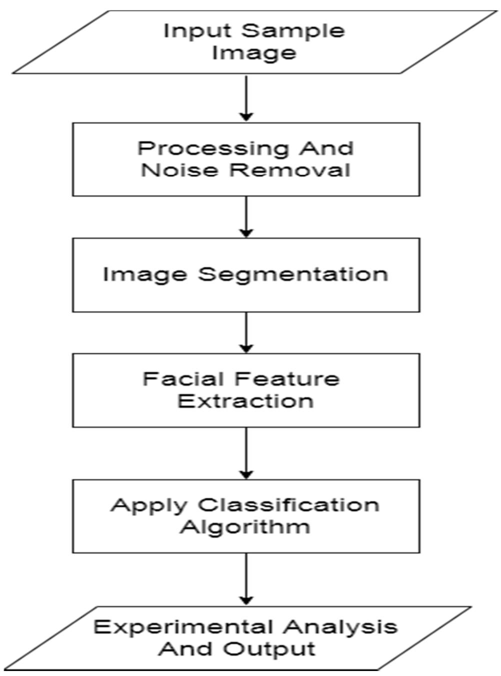


Fig. 10. Emotion Detection Data Flow Diagram

First take the picture of the user, then remove the noise in figure 10. Then just identify one person's face and apply the hair functions. Then adjust the image to match the previous training data set. Use the Python Keras library here. It works with the Convolutional Neural Network (CNN). CNN works on a sequential model. It also uses some levels like Conv2D, MaxPooling2D, AveragePooling2D, Dense, Activation, Dropout and Flatten. After the approach, these levels select the emotion from the classification set. This is the final edition.

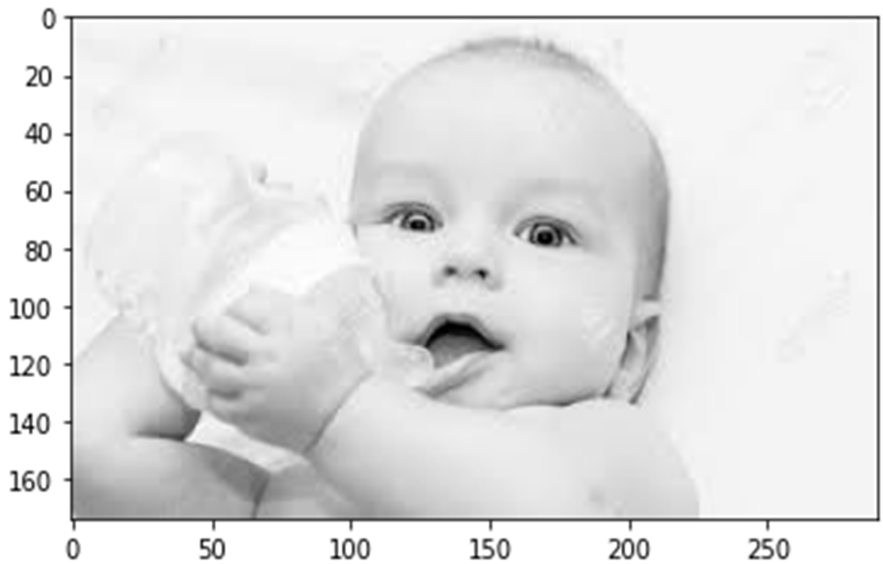
After the preprocessing (if necessary), the normalized face image is displayed to the feature extraction part to find the key features used for classification. In other words, this module is responsible for creating a vector of features good enough to represent the image of the face. After this comparison, the image of the face is classified into one of the seven expressions (anger, contempt, disgust, fear, happiness, sadness, surprise).

4. RESULTS AND EXPERIMENTAL ANALYSIS

The first major challenge was the confined measure of information for preparing a broad framework. This needs to defeat for framework in nature. Move learning is the most prevalent response to this. In this methodology that was begun from pre-prepared strategy and calibrated this model with the put-away information which is gathered from a genuine world. A progression of starter investigations affirmed the presumption that face acknowledgment would serve better in highlight extraction in figure 11. There are models where such systems are effectively utilized.

Machine learning algorithms work well on the datasets that have a couple of hundred highlights or segment. The algorithm successfully classifies an image and classify the sentiment of the image and choose the match emotion for the image. The reason behind choosing the deep learning classifier is that the classifier runs data through several layers. And a deep learning algorithm can be useful for less unpredictable issues since they gain admittance to an immense measure of information to be compelling. For pictures, the regular benchmark for preparing profound learning models for broad picture acknowledgment approaches more than 14 million pictures. For perfect visualization of emotion detection pattern analysis, it used a decision tree. In the decision tree, the character is represented by the nodes and layers, and also the outcome of the experiment is represented by the branch.

The advantage of the decision tree is that it is very helpful and easy to visualize the emotion and interpret the result in figure 12. The working process of a decision tree is easy to understand. If it has been classified the data according to their movement, reactions, and order which ideally different types of emotions. This also has been classified into trees and subtrees which reflects that Whether the person is sad, angry or happy, etc. if this could find something that can categorize their using these methods more simply. To do this it has been used retrain method that memorized the pattern and satisfies the condition. When any of the condition is satisfied it carry on to the end of the tree. However, if none of the conditions satisfy the intermediate condition, it will stop checking and say "The emotion cannot be identified. The emotion is unknown".



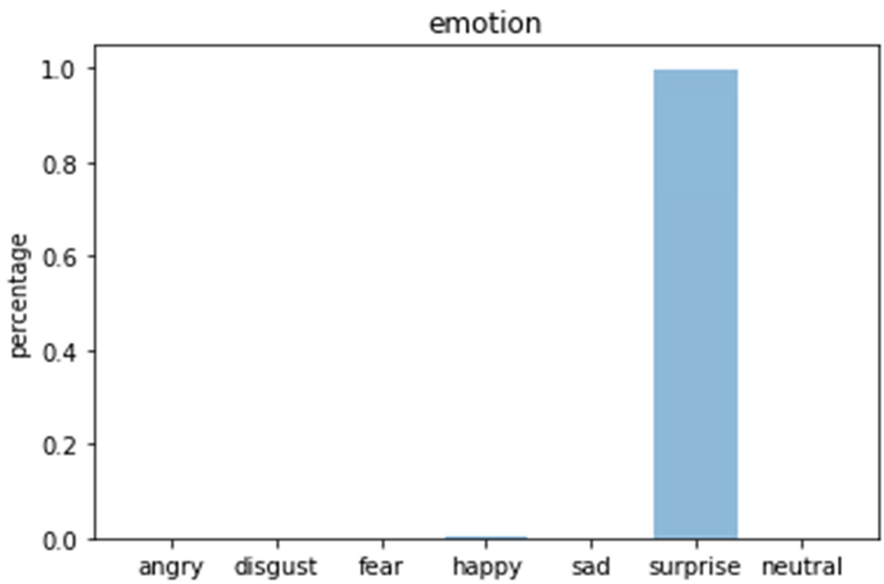


Fig. 11. Expression with surprise emotion

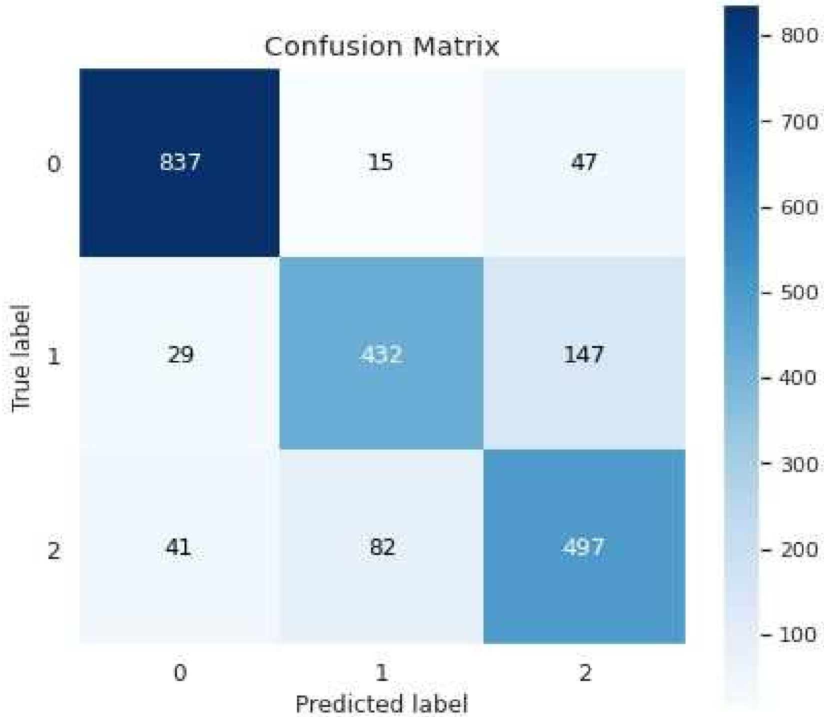


Fig. 12. Confusion matrix of CNN algorithm

Emotions are complicated to understand. There are different kinds of expression for the same emotion. Different people give different kinds of expression for the same kind of emotion. Modern-day machine learning technology can help law-enforcement authority to detect emotion so the machine can understand the emotion of humans and more behave and act like humans. This data for emotion came from different online and offline media. Such as Google, kaggel.com site. Friends and family, random people, etc. This is used Keras library to initially classify and analyze the emotion and got that data. Then with the help of Haar features and Numpy, It identifies the emotion. And with the help of platform anaconda. It generates the output from the raw data where the result is going to show in real-time.

The hierarchical data mining procedure like decision tree helps to generate probability decision by calculating various probability decisions by calculating various characteristic which is initially used to identify the emotion pattern. Along with offline and online data collection, it also conducted an effective field study to gather more people and various kinds of people and various emotional deferent expressions lots of different faces. In online data collection, the data set is taken from kaggel.com. They provide quality data sets. They converted the images into pixel grayscale and use the numerical number of the images. So, it gives the quality data and the batter result. Both of the experts believed that this analysis of sentiment could help identify emotion more accurately and help to take accurate actions on behalf of accurate emotion identification. It would provide more knowledge about different types of expression of their sentiment as well as the percentage of each existed various kinds of emotions.

While completing this work, we found that a large quantity of test data and keywords are needed if it wants to get greater accuracy. A lack of a good quantity of raw data is also required to extend the research work. A high configuration graphics processing unit (GPU) qualified computer is also required if this wants to process a large quantity of test data in the shortest time. So, if this gets adequate data along with a high-performance computer, it will be easier for that to rise the accuracy to more than 93% in figure 13. It will also be able to use that system for a different platform for a different outcome and help to determine the emotion expression pattern in figure 14.

```
Number of instances:  35888
Instance length:  2304
28709 train samples
3589 test samples
Epoch 1/25
256/256 [==============================] - 390s 2s/step - loss: 1.7599 - accuracy: 0.2730
Epoch 2/25
256/256 [==============================] - 393s 2s/step - loss: 1.5138 - accuracy: 0.4065
Epoch 3/25
256/256 [==============================] - 392s 2s/step - loss: 1.3536 - accuracy: 0.4787
Epoch 4/25
256/256 [==============================] - 394s 2s/step - loss: 1.2466 - accuracy: 0.5215
Epoch 9/25
256/256 [==============================] - 393s 2s/step - loss: 0.9376 - accuracy: 0.6479
Epoch 10/25
256/256 [==============================] - 393s 2s/step - loss: 0.8871 - accuracy: 0.6696
Epoch 11/25
256/256 [==============================] - 392s 2s/step - loss: 0.8187 - accuracy: 0.6943
Epoch 16/25
256/256 [==============================] - 391s 2s/step - loss: 0.4975 - accuracy: 0.8158
Epoch 17/25
256/256 [==============================] - 394s 2s/step - loss: 0.4618 - accuracy: 0.8302
Epoch 23/25
256/256 [==============================] - 390s 2s/step - loss: 0.2680 - accuracy: 0.9030
Epoch 24/25
256/256 [==============================] - 389s 2s/step - loss: 0.2493 - accuracy: 0.9190
Epoch 25/25
256/256 [==============================] - 390s 2s/step - loss: 0.2389 - accuracy: 0.9372
```

Fig. 13. Output of the proposed neural set

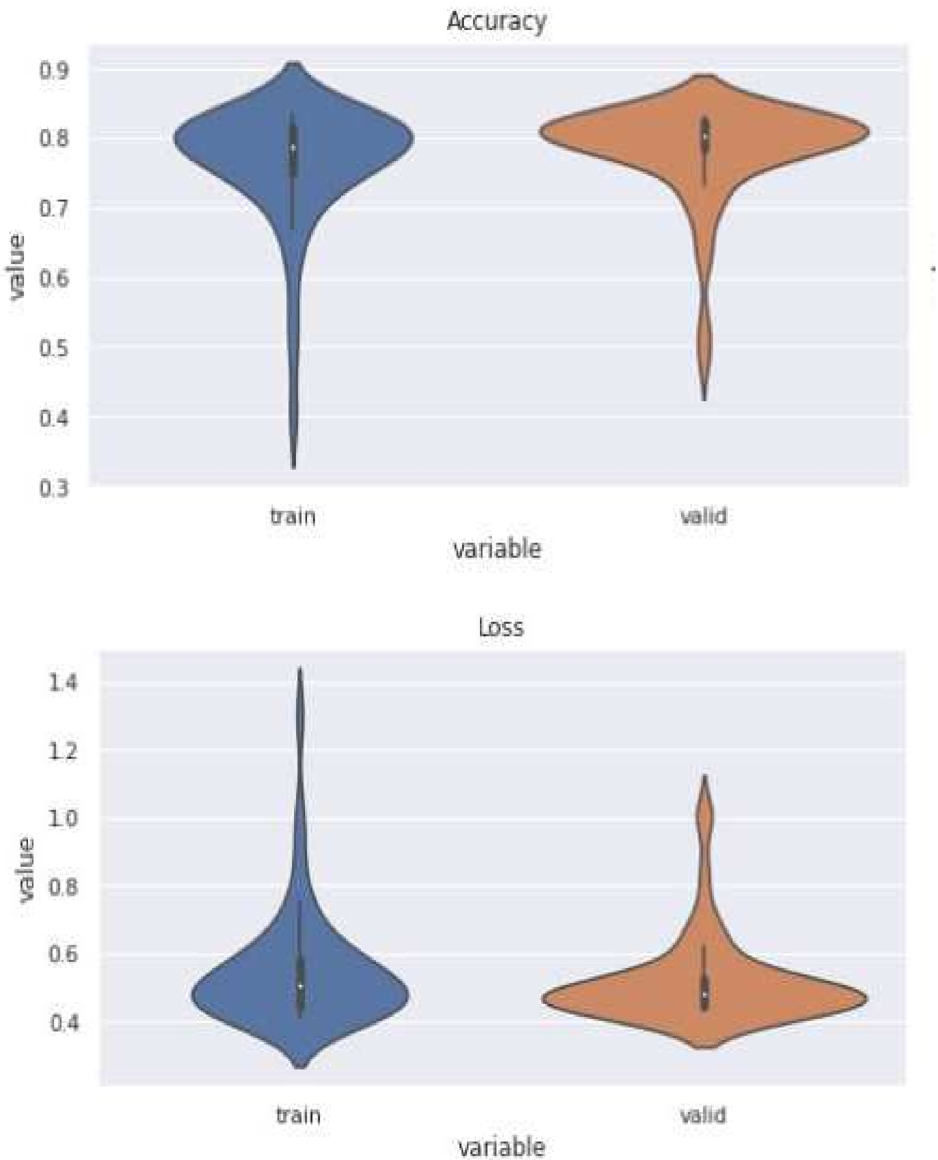


Fig. 14. Accuracy with varience of Epoch

5. CONCLUSION

By taking into account the whole process precise results were given by Neural Network in comparison to traditional machine learning approaches and gave 98.75% of accuracy than other models. The classifier can help in cataloging of Sadhu and Cholit languages of Bangladesh. As Bangladeshi literature is enriched with Sadhu language so most of the novels present from ancient era are in Sadhu language and this approach can help in their translation more accurately as its highly uncommon for present generation. That is why it can be converted to Cholit so that people can get familiar to old literature. An experienced human can often identify another human's emotions by analyzing and looking at him or her. However, in this modern age machines are becoming more intelligent. For the time been machines are trying to act more like humans. If the machine has been trained on how to react on behalf of the human sentiment at that time. Then the machine can behave and act like a human. On the other hand, if the machine can identify the emotion it can prevent lots of occurrences too.

With increased proficiency and errorless computation emotion, data mining can facilitate accurate expression patterns enabling machines to find and act more like humans effectively. To determine the emotion expression patterns this thesis is created or framework with comprehensive research and field works. This followed the framework step by step to get the expected outcome. To follow the framework and to identify the emotion expression patterns more effectively and used deep learning CNN algorithm along with Keras, Tensorflow, and retraining concepts.

With these techniques, it was possible to identify emotions, type of emotion in the real image. To delineate the result and procedures more visually and this has also introduced decision tree techniques which helps to decide which emotions percentage is high and which emotions percentage is low. Now the high percentage of emotions get the most possible accurate emotions. And the low percentage of emotions get the low chance of existence. With this discovery, it is now possible to determine accurate emotions. And machines can identify emotion more accurately and on behalf of that, they can give a proper reaction and also can help to prevent the same unwonted occurrence. This machine can also become the replacement of a human.

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