

Hand-Drawn Emoji Recognition using Convolutional Neural Network

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Abstract—Emojis are like small icons or images used to express our sentiments or feelings via text messages. They are extensively used in different social media platforms like Facebook, Twitter, Instagram etc. We considered hand-drawn emojis to classify them into 8 classes in this research paper. Hand-drawn emojis are the emojis drawn in any digital platform or in just a paper with a pen. This paper will enable the users to classify the hand-drawn emojis so that they could use them in any social media without any confusion. We made a local dataset of 500 images for each class summing a total of 4000 images of hand-drawn emojis. We presented a system which could recognise and classify the emojis into 8 classes with a convolutional neural network model. The model could favorably recognise as well as classify the hand-drawn emojis with an accuracy of 97%. Some pre-trained CNN models like VGG16, VGG19, ResNet50, MobileNetV2, InceptionV3 and Xception are also trained on the dataset to compare the accuracy and check whether they are better than the proposed one. On the other hand, machine learning models like SVM, Random Forest, Adaboost, Decision Tree and XGboost are also implemented on the dataset.

Index Terms—hand-drawn emoji, recognition, classification, convolutional neural network, CNN, pre-trained model, machine learning.

I. INTRODUCTION

As the world is advancing, people tend to spend more time on social media rather than the actual society. They share their thoughts, views, lifestyles, daily activities and many more on the social media and stay connected with other people and the community in that way. Man cannot express their feelings exactly just by writing them, it needs facial expressions to reveal those feelings. Emojis come in handy in that very case. Emoji is like a character which symbolizes the design of a thing without specifying the sound to say it that is applied in electronic messages. Emojis were first introduced in 1997 on Japanese mobile phones, became widely popular over the few years. They have become inseparable from the social media nowadays. In spite of not being a word, Oxford Dictionaries' made an emoji (Face with Tears of Joy) its word of the year

in 2015 [1]. That proves the popularity of emojis in present days.

Hand-drawn emojis are emojis that are drawn in any digital painting software or just in a piece of paper. With the advancement of technologies, digital devices have been taking various types of inputs from the users including voice, facial expressions, handwritten texts etc. All these experiments are done only for making the devices as well as the social media more user-friendly to the users. Due to providing the users with plethora of emojis on various social media platforms such as Facebook, Twitter, Instagram, Whatsapp, sometimes they find it really difficult to search their desired emoji. This problem could be solved by enabling them to draw the emoji and find the appropriate one. This could not only save a lot of time, but also make the users artistic. Google initiated its first handwriting input for text as well as emoji on android in 2015 [2]. Google had launched handwriting recognition earlier in the Google Translate app but that did not include emojis. In 2017, Gboard for Android introduced hand-drawn emoji recognition which enabled the user to draw emoji directly on the android screen [3]. Gboard could recognise the drawing of the user and show result for the drawing. This made it lot more interesting for the users to use Gboard.

In this research, we created the dataset by our own for the classes. We developed a system based on CNN model which could recognise eight different classes of hand-drawn emojis: Slightly Smiling Face, Smiling Face with Heart-Eyes, Neutral Face, Angry Face, Face with Tears of Joy, Winking Face, Face with Tongue and Frowning Face from the given input image and classify the emojis from the dataset. We also applied pre-trained CNN models and other machine learning techniques on the dataset to show the comparison among them. It proves the proposed CNN model's performance is the most effective among all the models. It has also been capable of giving a nearly equal accuracy rate for all the eight classes.

The related works performed on emoji recognition are briefly described in section II. Section III shows and presents

the methodology of our proposed system. Following that, section IV discusses about the eight classes of emojis recognized in the system and the dataset we built. Section V and section VI represent system implementation and result and discussion respectively. The comparison of the pre-trained CNN models and other machine learning methods are also displayed in result and discussion. Eventually, the research comes to an end in section VII by giving the conclusion and future works that will be addressed.

II. RELATED WORK

There has not been many works done on hand-drawn emoji classification. In fact most of the works are done on emoji prediction from texts or sentiment analysis from emojis and texts. So, hand-drawn emoji recognition is kind of a newbie in the research world.

In 2018, F Barbieri, M Ballesteros et al. [4] predicted emojis from the texts and pictures of Instagram. They combined two synergistic modalities to create a model so that they could make a better emoji prediction system. Their dataset consisted of 299,809 posts and there were 20 emojis to predict. The highest F1 (62%) was found for the Love emoji.

BG Priya et al. [5] analyzed sentiments from the comments of Twitter with the help of KNN (K Nearest Neighbor) in 2019. They extracted features from the images of the emojis to recognise the emojis. They worked on 8 classes but got the best results for smile, anger and sadness achieving an accuracy of 80%, 70% and 65% respectively.

Xiang et al. [6] worked on emoji classification as well as emoji embedding cooperatively in 2017. They grouped the emojis and classified them in terms of p@1, p@5 and MRR evaluation metrics. They also proved that their system could meet the expectations of the practical system. They collected their dataset from the conversation of some microblog websites and used 20, 50 and 100 classes of emojis.

In 2019, Matsumoto et al. [7] predicted the emojis that were merged to sentences using Deep Learning Networks. They gathered the tweets of some users with the help of a Twitter API. Their method could overcome the limitations of text based methods.

Chen et al. [8] proposed a unique method which takes emoji prediction like a tool so that it could determine a sentiment based representation for any language in 2019. They analyzed three types of sentiments which are positive, negative and neutral. As the dataset, they used raw tweets and tweets having emojis from two different languages, French and English. They gained an accuracy of 69% for French tweets and 81% for English tweets.

Cappallo et al. [9] predicted emojis from texts and emojis with the help of state-of-the-art neural networks in 2018. They collected 25 million tweets from the Twitter to make their dataset. They also proposed a consideration for predicting an unknown emoji. Their image plus LSTM model gave highest accuracy of about 89.3%.

Hallsmar et al. [10] explored the viability of an emoji training heuristic for the analysis of sentiments in 2016. They used four

classes for the research work: Sad, Anger, Fearful and Happy. The dataset for each class was at least composed of 100000 tweets. The highest accuracy of 90% was found for the Anger class but about 40% of the sad tweets were misinterpreted as angry tweets.

Pohl et al. in 2017 [11] issued a problem of the entry of emoji by a research on the present condition of the implementation on emoji keyboard in Android phones. They created a semantic model with a dataset of 21 million tweets consisting emojis. Their model could achieve a good result determining a comprehensive relationship among the emojis.

An interesting work on emoji prediction was held on emoji prediction. Ccoltekin et al. [12] proposed that SVMs (Support Vector Machine) perform better than RNNs (Recurrent Neural Network) in terms of emoji prediction. They chose English and Spanish tweets containing emojis to predict the emojis. The dataset contained 500000 tweets in English and 100000 tweets in Spanish. The accuracy for English tweets was 35.99%. On the other hand, the accuracy for Spanish tweets was 22.3%. Both of them were achieved by using SVM.

III. METHODOLOGY

Although the system has been implemented with various CNN methods along with machine learning methods, it mainly focuses on the customized CNN model. System flow chart of the research is shown in Fig. 1.

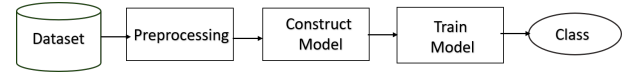


Fig. 1. System Flow Chart

With the help of a filter $w(q, r)$, convolution over an image $f(q, r)$ is defined by the equation (1):

$$w(q, r) * f(q, r) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(q - s, r - t) \quad (1)$$

As for the activation function, ReLU has been used in the convolution layer. To avoid the linearity of our model, ReLU has been applied in equation (2):

$$f(m) = \max(0, m) \quad (2)$$

Our CNN model has been supplied with 4000 images of 8 types of emojis. The model consists of 4 convolutional layers having 16, 32, 64 and 128 filters respectively while the size of the kernel is 2. The CNN model includes max pooling layers of 2*2 pool size after every convolution layer. Like the convolution layer, ReLU activation function is also included in hidden layers. There are dropout layers after every hidden layer. The dropout layers' value is marked on 0.5. To avoid overfitting, the dropout layer removes 50% neurons at random. Eventually, the output layer of the model has 8 nodes because of having 8 classes which classifies the images. As for the activation function, we have used SoftMax [13] in the model.

TABLE I
SYSTEM ARCHITECTURE

Contents	Details
1st Conv Layer 2D	16 filters size 2x2, ReLU
1st Max Pooling Layer	Pooling Size of 2x2
Dropout Layer	Excludes 50% neurons at random
2nd Conv Layer 2D	32 filters of size 2x2, ReLU
2nd Max Pooling Layer	Pooling size of 2x2
Dropout Layer	Excludes 50% neurons at random
3rd Conv Layer 2D	64 filters of size 2x2, ReLU
3rd Max Pooling Layer	Pooling size of 2x2
Dropout Layer	Excludes 50% neurons at random
4th Conv Layer 2D	128 filters of size 2x2, ReLU
4th Max Pooling Layer	Pooling size of 2x2
Dropout Layer	Excludes 50% neurons at random
Output Layer	eight nodes for eight classes, SoftMax
Optimization Function	Adam
Callback	ModelCheckpoint

$$Softmax(m) = \frac{e^j}{\sum_i e^i} \quad (3)$$

As the model optimizer, we have used Adam [14] in our system and in case of the loss function, we have used Categorical Crossentropy. ModelCheckpoint is also added as callback function. The CNN model which has been composed for this study is illustrated in Table I

IV. DATASET

A. Characteristics of the Emojis

There are eight classes of emojis used for the research. They are Slightly Smiling Face, Smiling Face with Heart-Eyes, Neutral Face, Angry Face, Face with Tears of Joy, Winking Face, Face with Tongue and Frowning Face. Small descriptions about these emojis are collected from emojiopedia [15] and given below:

1) **Slightly Smiling Face:** This emoji represents a yellow colored face with the eyes giving a slight smile. The emoji is used to express a positive and friendly view but sometimes can have a ironic meaning too.

2) **Smiling Face with Heart-Eyes:** This emoji is a face with a wide smile. It has two hearts in place of its eyes. It is used to show love for a person or a thing. It also expresses adoration.

3) **Neutral Face:** Neutral face emoji is a face with two open eyes with a closed mouth. It conveys a flat expression when there is nothing to say. It is also used to show that it is better to keep the mouth shut in that situation.

4) **Angry Face:** This emoji is a face with a frowning mouth giving a furious expression. The eyes are shown in a way which are giving a grumpy stare. The emoji is used to express anger on a person or a thing.

5) **Face with Tears of Joy:** Face with Tears of Joy is an emoji showing laughter. This emoji has a widespread mouth, two grinning eyes with two teardrops coming out of the eyes because of the laughter. This is one of the most popular emojis till now extensively used in all social media.

6) **Winking Face:** This emoji is a face with slight smile and naughtiness. One eye is open and the other one is closed to give the perfect wink. It is used in jokes or flirt texts.

7) **Face with Tongue:** Face with Tongue emoji conveys silliness or a sense of kidding. It is a face with the eyes open and the tongue out of mouth. It is used to convey that someone has done or said something very stupid, foolish or childish.

8) **Frowning Face:** Frowning Face is simply used to express sadness, sorrow, depression or misery. It is a completely opposite emoji for slightly smiling face emoji. It is also used to show guilt or to ask forgiveness.



Fig. 2. Pictures of the Emojis

B. Data Collection

We made a local dataset for this research as there is no standard dataset for hand-drawn emojis. Each class has 500 images of the particular emoji. So, there are 4000 images in total in the dataset. The emojis are drawn in various drawing softwares such as Adobe Illustrator, Adobe Photoshop, Microsoft Powerpoint etc. Some emojis were freehand drawings, some were drawn using shapes. Besides, almost 400 images were drawn in paper and then captured to get added in the dataset.

V. SYSTEM IMPLEMENTATION

Our proposed system's codes have been set down and developed by using python in Google Colaboratory [16]. The libraries that we used in the system are Keras [17], Tensorflow [18], NumPy [19], and Matplotlib [20]. Tensorflow has been used as the backend of the experiment and keras has been used in the system to provide built-in functions such as activation functions, optimizers, layers etc. NumPy is used for numerical analysis. Sklearn is used for generating confusion matrix, splitting train and test data, modelcheckpoint, callback function etc where matplotlib library has been used to make the graphical representations, such as confusion matrix, loss versus epoch graph, accuracy versus epoch graph, etc. When an image is provided as input in our system, the image is preprocessed. The preprocessing is done in the exact way when the model is being trained. Then it predicts the class based on the processes.

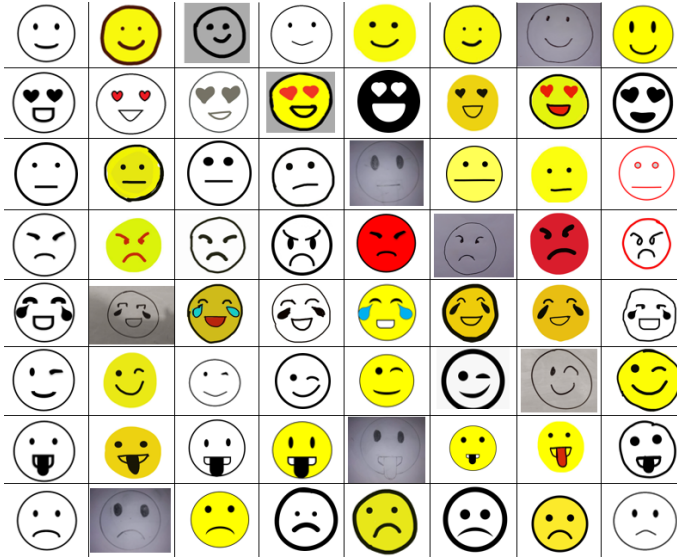


Fig. 3. Dataset Samples

VI. RESULT AND DISCUSSION

A. Proposed CNN Model

Our proposed system gives an amazing accuracy rate for each class resulting in an overall accuracy which is 97%. The accuracy, precision, recall and f1-score for the individual classes are displayed in Table II. We can see that winking face has the **least accuracy of 93%**. On the other hand, slightly smiling face and smiling face with heart-eyes have the **highest accuracy of 98.3%**. We can see that our constructed CNN

TABLE II
RESULT OF THE PROPOSED CNN MODEL

Class	Accuracy	Precision	Recall	F1-Score
Slightly Smiling Face	0.983	0.98	0.99	0.98
Smiling Face with Heart-Eyes	0.983	0.97	0.99	0.99
Neutral Face	0.973	0.97	0.98	0.97
Angry Face	0.977	0.99	0.96	0.98
Face with Tears of Joy	0.98	0.97	0.99	0.98
Winking Face	0.93	0.93	0.93	0.93
Face with Tongue	0.98	0.99	0.97	0.98
Frowning Face	0.973	0.97	0.98	0.97

model has been able to give an excellent result for each class. The confusion matrix of the model is shown in figure 4. X-axis of the confusion matrix corresponds to the predicted level and y-axis corresponds to the true level. The training accuracy vs validation accuracy of the model is presented in figure 5. 250 epochs are used to train the model. It is visible that both the training and validation accuracy keep increasing until the end.

The training loss vs validation loss of the model is displayed in figure 6. It shows that the training loss and the validation loss keep decreasing with the epochs.

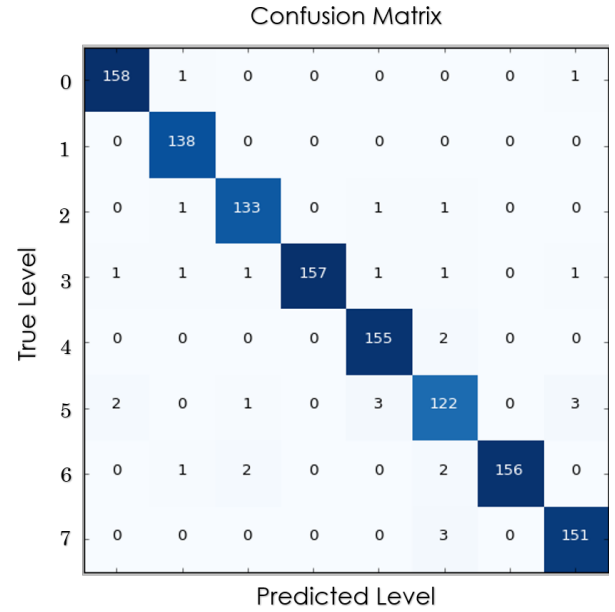


Fig. 4. Confusion Matrix

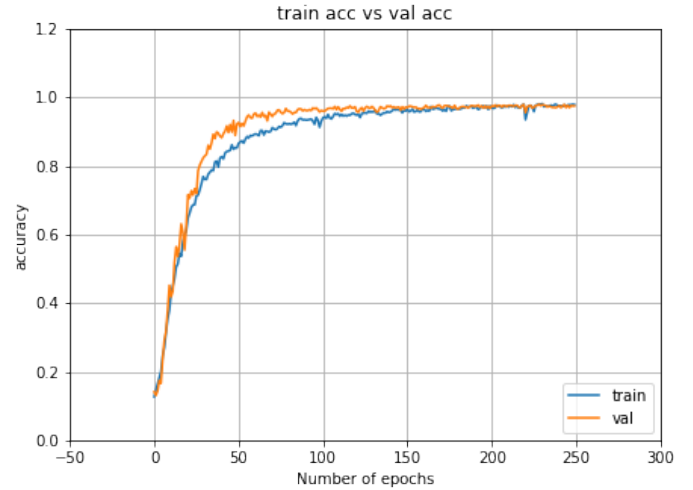


Fig. 5. Training Accuracy versus Validation Accuracy

B. Comparison of Pre-trained CNN Models

Our dataset have also been experimented by some pre-trained CNN models like VGG16, VGG19, ResNet50, MobileNetV2, InceptionV3 and Xception to classify the emojis. InceptionV3 achieved the best accuracy, whereas MobileNetV2 gave the lowest accuracy. Table III shows the accuracy, precision, recall as well as f1-score for the pre-trained models. The confusion matrix for InceptionV3 has been shown in figure 7. The training accuracy versus validation accuracy graph and the training loss versus validation loss graph are shown in figure 8 and figure 9 respectively.

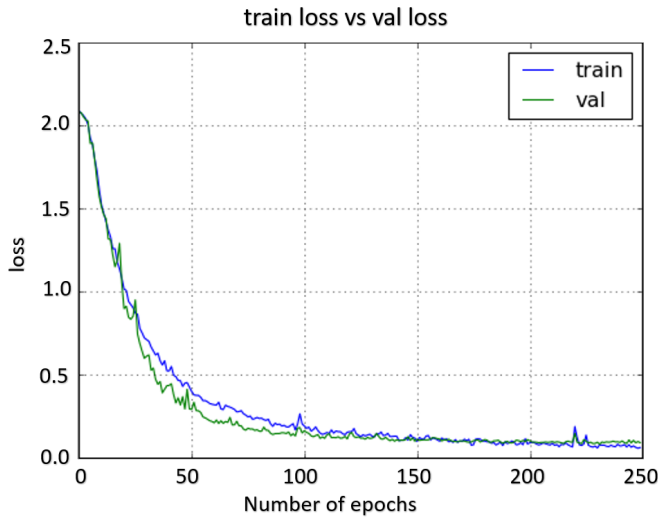


Fig. 6. Training Loss versus Validation Loss

TABLE III
RESULT OBTAINED FROM THE PRE-TRAINED CNN MODELS

Model	Accuracy	Precision	Recall	F1-Score
VGG16	0.907	0.909	0.906	0.907
VGG19	0.912	0.915	0.910	0.912
ResNet50	0.905	0.908	0.903	0.906
MobileNetV2	0.870	0.877	0.867	0.872
InceptionV3	0.941	0.941	0.939	0.940
Xception	0.922	0.928	0.919	0.924

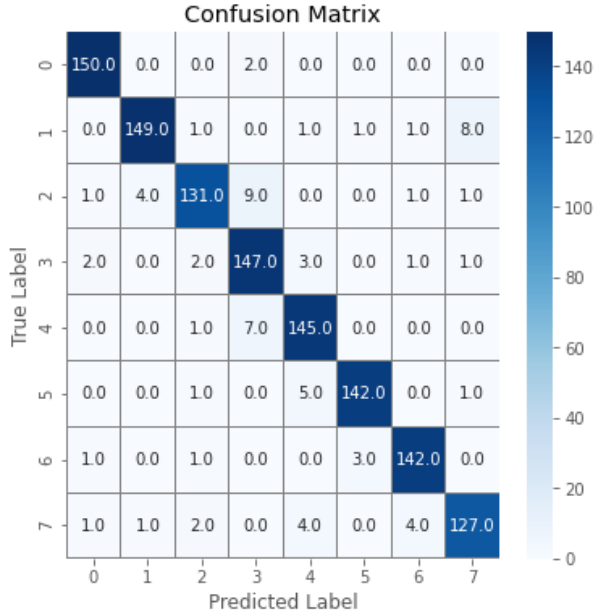


Fig. 7. Confusion Matrix

C. Comparison of Machine Learning Models

The dataset is also trained by some machine learning models like SVM, Random Forest, Adaboost, Decision Tree and

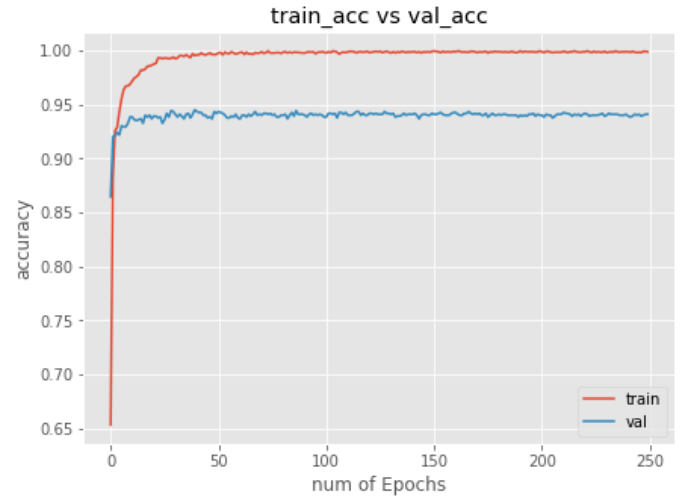


Fig. 8. Training Accuracy versus Validation Accuracy

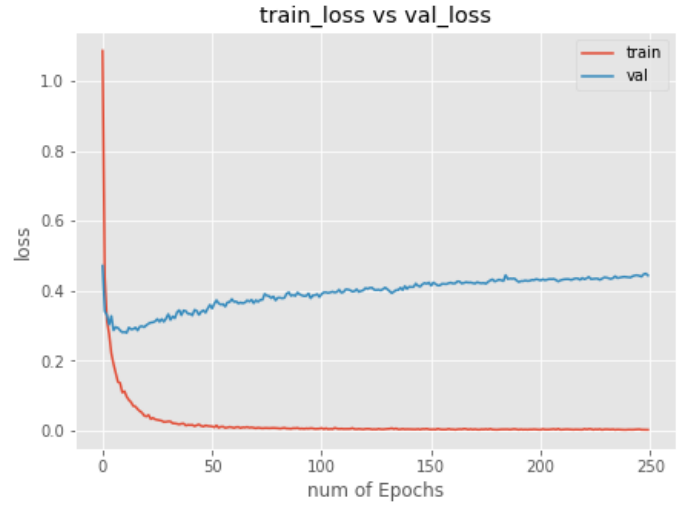


Fig. 9. Training Loss versus Validation Loss

XGboost. Table IV shows the accuracy, precision, recall as well as f1-score of the machine learning models. We can see that Random Forest classifier gives the best result on the dataset.

TABLE IV
RESULT OF THE MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.67	0.667	0.666	0.667
Random Forest	0.77	0.77	0.767	0.768
Adaboost	0.61	0.611	0.612	0.611
Decision Tree	0.61	0.606	0.610	0.606
XGboost	0.73	0.735	0.732	0.731

After discussing all the results from various models of CNN and machine learning, we can clearly see that our proposed CNN model surpasses all of them and gives the best result.

VII. CONCLUSION AND FUTURE WORK

An image classification system for hand-drawn emojis has been introduced in this research paper for enabling the users to look for their preferred emoji on social media softwares. Though a standard dataset was not available online for hand-drawn emojis, we took the initiative to make a local dataset for conducting the research work. The dataset could be shared with other authors interested in performing research on hand-drawn emojis. Our proposed CNN model gave the highest accuracy rate outperforming other CNN or machine learning models. We already know that CNN models perform better than machine learning models in terms of image classification [21], [22], [23], [24] and also in speech recognition [25]. Although our proposed model and the system have fairly done their job in classifying hand-drawn emojis, some works can still be done in future to make the system even more powerful and robust. We can apply our model on a large amount of classes as there are hundreds of emojis on different social media platforms. The system can be better if it can take input images in real time and identify the emoji immediately. Besides, more hand-drawn images can be added to the dataset to make the classification stronger. Moreover, BRBES could be used to collaborate with deep learning and make the system more powerful [26], [27], [28], [29], [30]. We will try to address these issues in future to make the hand-drawn emoji classification a standard one.

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