Temporal Colour-Coded Facial-Expression Recognition Using Convolutional Neural Network

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Abstract. This research primarily aims to solve the problem of the high suicide rate in NZ; in this project, we plan to implement an AI-based recognition system for the long-term mental health issue for discovering potential suicidal population in NZ society. Visual data (CCTV video footages) possesses affluent and bountiful information; however, the amount of data grows explosively; thus we often fail to capture the patterns and extract meaningful featured data for any reliable analysis. Moreover, AI-detected human facial microexpressions are usually ambiguous and return with various uncertain patterns. It is extremely tough to identify and verify the emotions of somebody in the last few minutes, hours, days, weeks, or months. In a nutshell, it is very challenging to assess the depression so as to predict their suicidal probability. Pertaining to solve this problem, we will design a novel temporal expression recognition system based on the accumulation of seven colour-coded human emotional expressions, namely, anger, disgust, fear, happiness, sadness, surprise, and neutral. We propose to use various colour dots (rain-drops) to replace the feelings of people. We assume that, just like the colour, people have three primitive emotions: joy (green), sadness (blue), and anger (red). The mixture of these will lead to other feelings: anger + joy = surprise (yellow), anger + sad = scare (purple), joy + sad = disgust (cyan), and when these three primitive feelings are additive, we get a neutral state (white). Long-term feelings are emotions accumulated overtime, digitally presented by using any drops of colours on to a white canvas. Each canvas can be the feeling of someone in a predefined period (the last five minute, for instance). By implementing this, the emotions of target persons over the previous one month could be effectively packed down into a movie of approx. 2 h (60 Hz). At any time, such a video could be assessed by using AI algorithms for stress level assessment (in the last one month) so as to decide the requirements of mental treatment.

Keywords: Computer vision · Object detection · Deep learning · Facial expression recognition

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1 Introduction

1.1 Research Background and Significance

New Zealand has one of the highest teenage suicide rate in the developed world [1]. While the numbers are staggering, they are nothing new. Now, scientists believe there is a significant link between mental health and suicide risk [2]. That is, if a person has a mental health problem, they are more likely to commit suicide. At the same time, poverty, domestic violence, drug or alcohol abuse and despair are also objective factors that affect mental health (increase of depression).

Almost one-third of New Zealanders own personal experience of mental distress; Māori and young adults aged 18 to 24 years have higher rates of mental distress. Patients with depression have suicidal thoughts, and suicide is the most dangerous symptoms of depression. Hence, suicide is a severe mental problem in New Zealand. We have one of the highest teenage suicide rates among 41 OECD and EU countries. Even though there are a plethora of youth support centres and counselling services all over the country; many are ashamed to seek assistance. It could be more effective if we would like to accurately and automatically sense who are currently vulnerable to suffering this problem and necessitate to accommodate support.

Patient with depression have suicidal thoughts, and suicide is the most dangerous symptoms of depression. People with depression are depressed and pessimistic. It is easy to have suicidal thoughts when it is serious. They often feel lack interest, lack of mental and physical strength, and then their eyes are always with tears; they think that life is worse than death.

At present, the key to the check of suicide risk is to rely on people's mental health risk assessment [3], such as the existence of hidden psychological dangers, psychological crisis emergency assessment and so on. The presence or absence of hidden psychological trouble is a test to evaluate whether the individual has hidden psychological disorder and the severity of its existence.

Judgmental assessment of the emergency degree of psychological crisis mainly focuses on the judgment and its harm to oneself and others:

1. Whether he/she will commit suicide, self-harm, attack others or other dangerous behaviours.
2. Whether there are serious risks and hidden dangers of psychological problems that may break out at any time.

Thus it can be seen that the current assessment of the severity of mental health problems of suicides is subjective. It may be that the depressed person does not get the attention and intervention in the first place due to deliberate cover-up during testing or the inexperience of the psychologist. It is also possible that because people around do not care enough about the person concerned, they do not find the hidden psychological problems, so they do not control the risk factors in the first time and carry out effective psychological intervention and treatment.

Deep learning methods, especially in the field of image classification and recognition, have achieved fruitful results in recent years [5], the technique of extracting image features by training facial expression recognition (some are seen in Fig. 1) has attracted

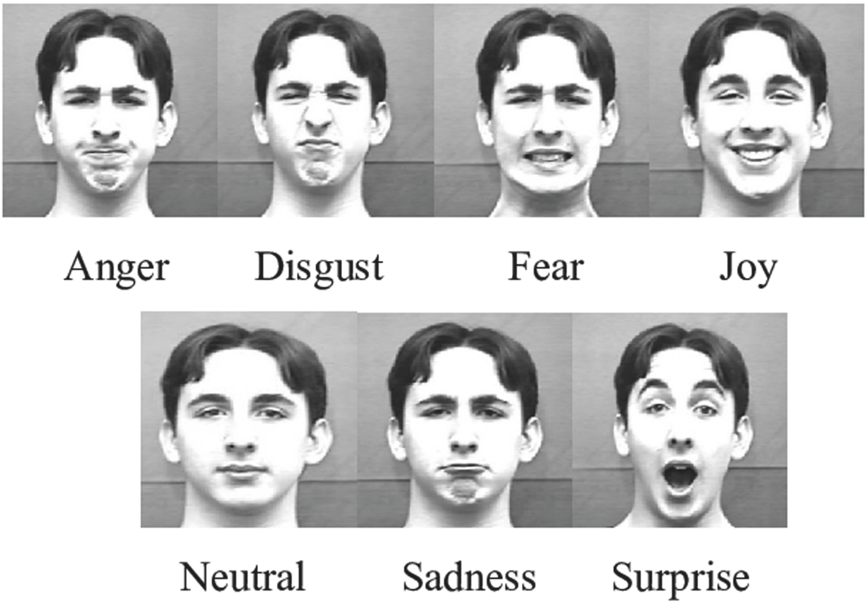


Fig. 1. Some examples of seven basic human emotions [4]

great attention [6–8]. Among many deep learning algorithms, convolution neural network (CNN) technique is more effective in learning the most effective deep features of images [9]. Because CNN has the advantages of autonomous learning of graphic components, compared with other visual-based methods, it can detect people's current psychological state in the first time. The question is "can CNN help efficiently detect depression by finding the presents of negative facial expression?"

The goal is to identify the vulnerable population better and provide a good foundation for follow-up psychological counselling work. This transformative research explores a unique theory of the feasibility of converting a massive fuzzy quantity of temporal emotions (individuals or a community) into a more manageable, intuitive, visual representation of mental health status. Today, Artificial Intelligence (AI) benefits us to recognise micro-expression via cameras or CCTV (i.e., closed-circuit television) systems, e.g., smile detection. However, these expressions are captured in a sequence of video frames, or in a fraction of a second (most cameras nowadays acquire 30–60 frames per second). In contrast, depression is a long-term feeling; negative emotions must be accumulated over a long time (namely, weeks, months, or even years). It sluggishly drains the optimism, energy, and drive; and produces suicidal thoughts bit by bit. Therefore, we will have to care for someone for an extended period to identify for any those at risk.

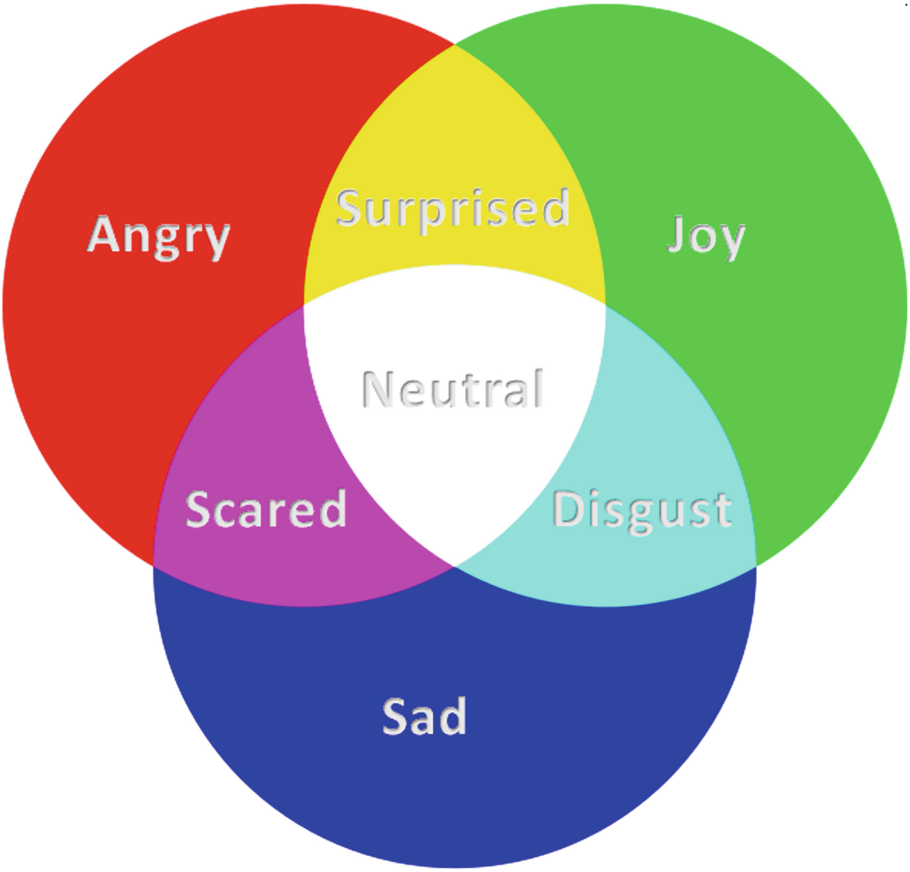


Fig. 2. Proposed colours of seven emotions

1.2 Research Objective and Plan

This paper aims to use image processing and CNN; to recognise long-term negative facial expressions, and thus, help estimate the likelihood of someone who may commit suicide (after months of depression). We hope that it could be used to help reducing the suicide rate in New Zealand and even internationally.

However, it is only easy for computer vision to recognise micro-expression, e.g. expression (smile detection, for instance) presented only in a fraction of a second (30–60 frames per second). After a long period, the data collected could be accumulated and become extremely large for any reliable analysis. Moreover, micro-expressions are often returned with various uncertainties. It is hard for it to know the true feeling (could be up and down) of someone in the last few minutes, hours, days, weeks, or months. In short, it is very challenging to assess the stress level of someone to conclude for the sucidural probability.

We propose to use various colour dots to replace feelings of people. We assume that just like colour space, people have three primitive feelings: joy, sadness, and anger. The mix of these feelings will create other feelings: anger + joy = surprise, anger + sad = scare, joy + sad = disgust, and when these three primitive feelings are added together, we get neutral feeling. To simplify it, we create a colour additive table as shown in Fig. 2.

Long-term feelings are emotions accumulated overtime, presented by painting many colour dots on to a white canvas. Each canvas can be the feeling of someone in a pre-defined period (the last five minute, for instance). By doing this, the emotional feelings of target persons during the previous one month could be effectively compressed into a movie of approx. 2 h (60 Hz). At any time, such a film could be assessed by AI for stress levels changed to make some decisions for the requirement of mental treatments. The details of designs, implementations, and testing results will be further discussed in the next few sections.

The idea of converting complex human emotions into colours is unique. We have a goal to extend it into a commercial product - an anger management IoT device. There are several research impacts on NZ:

– The IoT device could help reduce the depression, stress levels, and the suicide rate in NZ; we would like to offer the use of this on vulnerable individuals who are currently receiving mental health services through their GP or family doctor.
– The research helps create a more healthy working/teaching/learning environment (e.g. classroom, office, etc.). The device displays the average feeling (negative/positive) of a room/office/lab for an extended period; this helps management to think of applying necessary actions (e.g. team-building activities) to raise the healthy working environment for NZers. We will meet and talk to these clients about the pros.; we will offer the use of the devices in classrooms and offices.

2 Backgrounds and Related Works

2.1 Basic Emotions of Human Beings

In 1971, psychologists Ekman and Friesen put forward six basic emotions of human beings [10], namely Surprise, Sadness, Anger, Fear, Disgust and Happiness. In order to describe facial expressions, different methods of facial expressions were born. Facial action coding system (FACS) was proposed [11], which can distinguish different facial expressions according to the movements of facial muscles and muscle groups. Facial animation parameters (FAPS) is another expression encoding method [12], which describes facial expressions according to the movement of facial features.

Usually, people's emotion is expressed through the combination of changes in each part of the facial muscles. However, people will hide real disguise emotions in particular circumstances, such as lying or negotiations. The consequent facial expressions do not reflect the true inner feelings; the study found that the facial will reveal a small, local, duration within half a second of facial expression [13]. Unlike regular facial expressions, the micro facial expression is entirely spontaneous, unable to forge or suppressed, can reflect the real emotion. According to the research of the Ekman et al. [14], this micro-expression can be divided into six basic categories: happiness, sadness, anger, surprise, disgust and fear.

2.2 Available Facial Expression Database

Many have constructed models of CNN by training and learning fatigue expressions from expression databases. CNN generally requires a large number of sample data; however, due to identity protection, not many available fatigue expression databases could be found easily. Some are listed below, and they are widely used at present.

CK+ Expression Database. The CK+ emoji database is an extension of the Cohn-Kanade database and was released in 2010 [15]. The CK+ database includes 123 sub-folders, with a total of 593 emoji images. The information on each picture contains the classification label. In this total of 593 photos, 327 of them are with the expression classification label, including the depressed expression and non-depressed expression.

Fer2013 Facial Expression Database. This facial expression database is composed of 35,886 face images; among them, the training image 28708, available test and private test are 3589 pieces. Each image is fixed by the size of 48×48 of a grey image, labelled with different kinds of expressions.

Colorferet Database. It contains more than 10,000 pictures of more than 1,000 people, each with different expressions, lighting, poses and ages. Also, this paper also took photos of fatigue expression to enrich the sample data. The images obtained through the above three methods included 10,000 face images, among which about 2,000 were fatigue expression images.

2.3 Existing Suicide Prevention Programs

In early 2018, the Public Health Agency of Canada announced a pilot program for a suicide prevention program [16] developed by the Canadian government in collaboration with Ottawa-based artificial intelligence company Advanced Symbolics. The pilot project will study and predict regional suicide rates by monitoring posts from Canadian social media accounts, including anything related to suicide. Throughout the trial, the researchers will analyze 160,000 social media accounts to identify a possible rise in community suicide rates across Canada. Government health authorities will be notified when AI technology predicts that suicide rates are likely to rise in certain areas. If the project is successful, AI could help Canadian health authorities indicate where the next suicide spike will occur, allowing interventions to be launched months in advance.

Back in 2011, Facebook developed an artificial suicide reporting system. Users can upload screenshots of suicide content posted by others for audit. Vetted, Facebook sends emails to suicidal users; they could chat online with a crisis intervention representative from the National Suicide Prevention Lifeline by clicking a link in the email, new ways to help those who are unwilling to call [17]. In 2015, the system allowed users to “tag” suicide-related content, allowing Facebook employees to speed up the review of posts and respond appropriately. In 2017, Facebook tried again to use the new “active detection” AI technology. The technology scans all posts for potential suicide attempts and, if necessary, sends mental health resources to users at risk of suicide or their friends, or to contact a local emergency hotline, without waiting for a user to report, to maximize help. The system has been successfully tested in the United States and plans to expand to more countries. For now, the assessment and management of suicide risk remain highly subjective, despite many attempts and efforts by researchers to use artificial intelligence to prevent suicide.

3 Design, Implementation, and Results

As said in the Introduction section, we plan to use three primary colours: red, blue, green, and their blending colours: yellow, cyan, magenta, and white; to present seven emotions. They are (1) anger; (2) disgust; (3) fear; (4) joy/happy; (5) sadness (6) surprise; (7) neutral. Therefore, the first step we need to do is to build a system that could classify these emotions. Using CNN, we need to build Emotional Expression Data-set with the seven classes as mentioned above.

3.1 Build of Emotional Expression Database via Web Crawler

In addition to the available database, we could extend the dataset by searching and downloading the Internet for emotional facial images through the Web crawler [18]. We crawl the web pages and download photos in batches while restricting the grasping content.

The crawling process is as follows:

– We simulate the browser to make a request: enter the URL to complete the request of the server and get the header information about the type, cookie, browser type and others.
– We get the server page response. If the server is running normally, we will receive real-time feedback, including data in binary format such as HTML, JSON string, picture, video.
– We analyse and store the content. If it is a picture, it is saved for further processing.

The emotional recognition based on micro-expressions consists of three steps, namely image pre-processing, feature extraction and emotion classification.

3.2 Image Pre-processing

In the practical engineering application, the source image data is broad in quantity and high in dimension. It is likely to contain a lot of noise interference information that is meaningless to the research. Therefore, it is necessary to pre-process the source image before model training to remove redundant noise, focus on crucial information, and compensate or recover some lost knowledge. Follows are some of our pre-processing steps.

Image Normalisation. The image normalisation step makes the face photos acquired under different directions and lighting conditions have consistency. Generally, the face images after face detection and alignment cannot be extracted directly for features. Scale normalisation is also needed to remove redundant information so that the image size is the same, and grey normalisation reduces the influence of light. The normalised operation can transform all images into a unified form, which is conducive to subsequent batch processing.

Scale Normalization. The size of face images after scale normalized face detection and alignment is different. Most machine learning algorithms require input is a fixed size. We apply scale normalization: images are extracted from the target face regions and cropping for the same size. We set the distance between the pupils of both eyes as d, take the midpoint of connection between the two pupils as the origin, take d in the horizontal direction, $0.7d$ in the vertical direction upward, and $1.7d$ in the downward direction, and then uniformly normalize it to 224×224 after shearing.

Grayscale of the Normalized Image. To reduce the calculation cost, we convert the colour images into gray-scale images. Grey image is a unique colour image where three-channel components are the same. Gray-scale image can effectively reduce the subsequent computation burden compared to coloured ones. According to the characteristic that the human eye has the highest sensitivity to green and the lowest sensitivity to blue, the value of each component weight and the transformation formula is shown:

$$Grey(i,j) = 0.3R(i,j) + 0.59G(i,j) + 0.11B(i,j) \tag{1}$$

Histogram Equalization. Finally, we apply histogram equalization to transforms the histogram of the original image into uniform distribution for image grey level normalization. This action makes image grey level clearer, improve the overall contrast, and weaken the influence of light on image analysis. In our system, histogram equalization improves not only the image contrast but also transforms it into a uniform distribution of pixel values.

3.3 ADA Boost for Face Detection

Among many machine learning methods, Ada Boost algorithm [19] is one of the most widely used face detections. Ada Boost algorithm learns the training samples repeatedly, weights the weak classifier with the lowest classification error rate obtained from each training, and then receive a classifier with better effect. Ada Boost classification detection algorithm for face detection does not rely on subjective prior knowledge and model construction, only extracts objective face image features, and realizes real-time detection with high timeliness according to the feedback results of feature classifier. Boosting is a method to enhance the accuracy of a weak classifier into a robust classifier after multiple classifications.

3.4 Model Trained and Deployment

After pre-processing and face detection, the facial features of depression can be trained and learned through Xception network [20]. Xception is an improvement on the Inception V3 model by Google. It replaces the convolution in Inception V3 with the deep separable convolution so that the convergence speed and recognition accuracy can be improved.

3.5 Temporal Colour-Coded Facial Expression Recognition

Assume that we have a reliable face recognition and emotion detection, which could return a result like such: Emotion = [anger: 10%; disgust: 5%; fear: 15%; joy/happy: 50%; sadness: 1%; surprise: 15%; neutral: 4%]. We could run an algorithm to paint the emotion onto our emotional canvas, as described in Algorithm 1.

Algorithm 1: Emotional canvas creation

```
initialization;
while there is a frame from video/webcam do
    face-detection();
    for each face do
        emotion-detection();
        for each emotion do
            fill-random-circle(emotion-colour, radius=certainty)
        end
    end
    save-canvas-as-a-frame();
end
Result: Write output as a video for further analysis
```

The colour dots are dropping down on the canvas at random locations, just like raindrops, with seven colours, as indicated in Fig. 2. Basically, the algorithm helps reduce the dimension of the temporal emotional expression of one-to-many people in a video footage down to only one 2D colour picture/video. It also eliminates the effect of storing all historical data, e.g. emotion detected too long ago will be filed away (by other more recent ones). Figure 3 displays two emotional canvas created from two video sequences, one with a lot of sadness moments (left figure), and the other one with loads of laughter (right figure). It is easy to notice the majority of blue dots in the sadness sample, while, the happy one contains significantly more green drops.

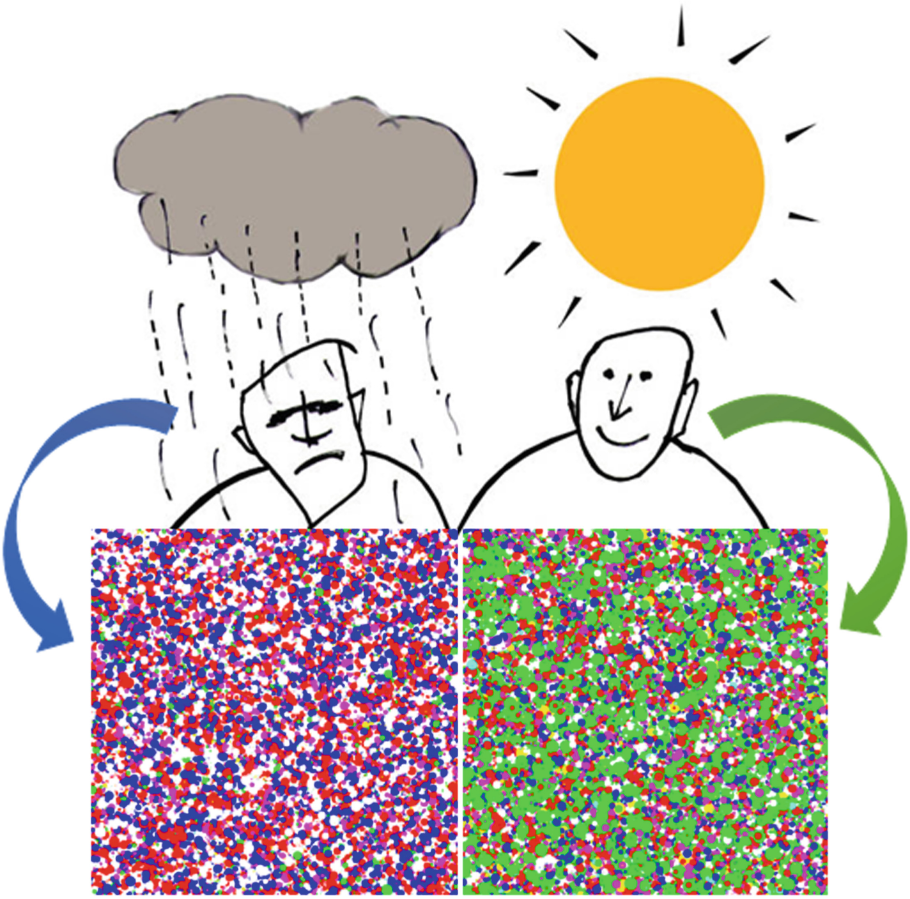


Fig. 3. Two samples of emotion canvas: a sad output (left) and a happy output (tight)

4 Results and Analysis

4.1 Accuracy of Emotional Facial Expression on Still Images

In the experiment, the cross verification method was adopted. The facial expression images of nine people were randomly selected as the training set and the facial expression images of the remaining one person as the test set so that each person's facial expression images were taken as a test sample. The experiment was conducted for ten times, and the average recognition rate of the ten experiments was finally accepted as the experimental result. We acquire photos with seven kinds of expression: Angry (AN), Neutral (NE), Disgust (DI), Feared (FE) Happy (HA), Sad (SA), Surprised (SU). The recognition rate of individual expressions and the overall recognition are recorded. Happy face returned with the highest accuracy (approx. 90%), while fear expression has the lowest detection rate (approx. 40–50%) (Table 1).

Table 1. Results for emotional detection

	True positive	True negative	False pos	False neg
Accuracy	81.82%	76.92%	18.18%	23.08%

4.2 Accuracy on Video Footages

It is challenging to quantify the accuracy of any emotional detection for an extended period or long video sequences. Therefore, we will not be able to conclude the accuracy in percentages. Instead, we try to run the system on various Youtube video footages, some are positive, with happy talks/comedies, some are negative, with cries and tears. After testing, we found out that the classification of the positive and negative primary trend is relatively robust. All positive video footages return a majority of green canvas; while negative video footages produce mostly blue and red dots.

To present the outcome, we have uploaded on Youtube two sample output:

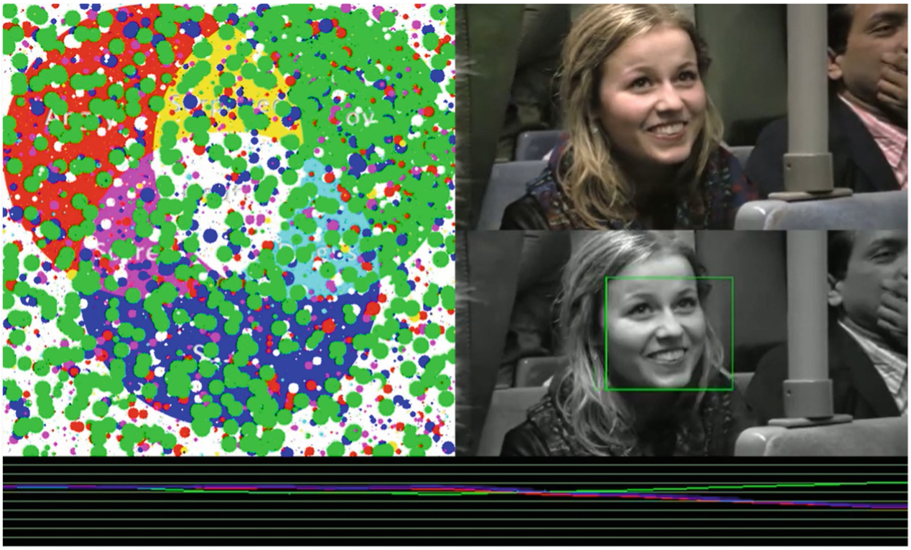
– A happy video at https://www.youtube.com/watch?v=KQuXGXkLwyg
– A sad video at https://www.youtube.com/watch?v=Y-Bul6oA5IY

Figure 4 displays screenshots of these two outputs. We recommend reviewers to access the Youtube links, to visualise the contribution of this paper. The left canvas is the live drops of emotional colour drops; the right is footage with face and emotional expression detection. The bottom part displays the expression trends using just three primary feelings, namely, happiness (green), anger (red), and sadness (blue).

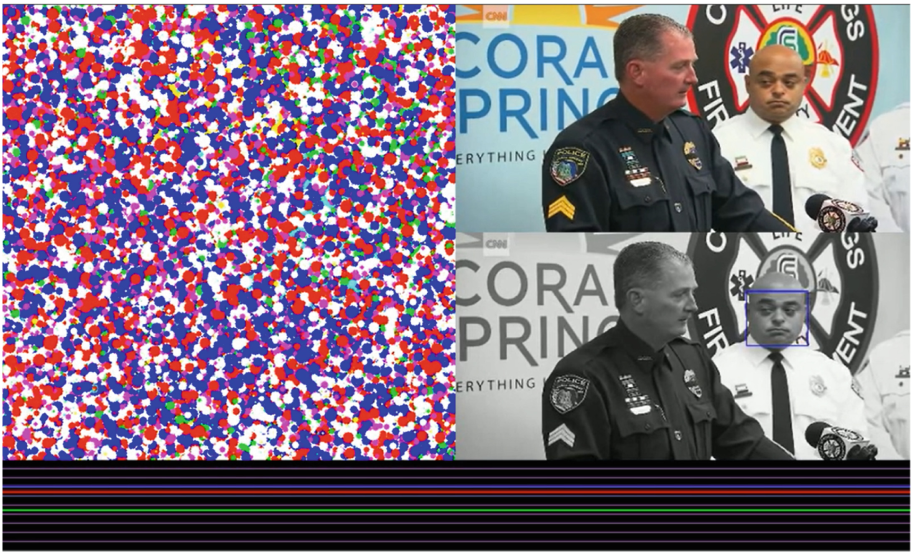
Besides the three main lines, there are ten other background lines, which colour is the mix of these three main lines (quantitatively):

$$Line(R, G, B) = (Anger, Happiness, Sadness)$$

By that, this single colour represents the average emotion at each moment of the video sequence. Thanks to it, we have successfully reduced the temporal emotional expression of a video sequence during any particular period down to only one single colour. If we want to quantify the emotion, we could just pick the Hue value, and the mixed feeling could expressively be represented.



(a) A happy video at https://www.youtube.com/watch?v=KQuXGXkLwyg



(b) A sad video at https://www.youtube.com/watch?v=Y-Bul6oA5IY

Fig. 4. Two samples of emotion canvas (Color figure online)

5 Conclusion, Limitations and Future Work

5.1 Conclusion

Aiming at the problem of high suicide rate, this project investigated the suicide situation both internationally and in New Zealand, and designed and implemented a suicide expression recognition system for suicidal people in the society. The aim is to identify the potential suicide population better and provide a good foundation for follow-up psychological counselling work. To quantify the mental health issues or likelihood of someone might commit suicide, we develop an algorithm that is capable to represent the complex temporal emotional expression of somebody down to just one single video sequence using colour raindrops.

The experimental results show that the recognition effect of the deep learning algorithm CNN is suitable to detect the seven selected types of expressions. Several video sequences and experiments are carried out to make the foundation for the feasibility of the project. Predictably, if the system can be successfully developed further, it will effectively quantify/detect a part of the suicide population, and thus reduce the suicide rate.

5.2 Limitations

Although this project uses cutting-edge modelling techniques, there are still many areas for improvement.

– Image preprocessing: Limited by hardware resources, the acquired expression image in this project is processed into a greyscale image of 48×48, and the parts outside the range are discarded. However, the retained image range will affect the features learned by CNN algorithm. To put it simply, the larger the enclosed image range is, the more features CNN can learn. Therefore, the accuracy of the model can be improved by increasing the capacity of retained images. Typical resolutions are 64×64 and 128×128.
– Data set expansion: CNN algorithm needs a large amount of data to learn the features in the data. In the case of less data, it isn't easy to get a good recognition effect. Therefore, the expansion of different types of emoticons, predominantly negative emoticons, is significant.

5.3 Future Works

This project design a system for negative expression recognition. With the assistance of other functions, the system can better achieve the goal of reducing the suicide rate.

– Questionnaire function: As a matter of fact, some potential suicide patients will not show evident expression. This phenomenon will limit the recognition effect of the system. But suicidal tendencies don't just affect the target's facial expression. They also affect the target's movement to answer specific questions. Therefore, combining some auxiliary functions, such as filling out questionnaires, and connecting the judgment results of other additional operations based on image recognition results, can effectively improve the recognition accuracy of the system.
– Image acquisition: Predictably, most people will not make blatant suicidal expressions when the system collects images. These predisposed emoticons are often inadvertently displayed to the outside world. In the future, the link of image acquisition can be optimized to contain users' expressions in certain activities.

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