Emoji-fied:

A Tangible Machine System for Exploring the Emoji-fication of Facial Expression Input

Peiyang Qin

23014796

MSc Creative Computing

University of the Arts: Creative Computing Institute

Supervisor: Adam Cole

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GitHub Link: Emoji-fied

Abstract

While digital communication is increasing, people are more and more relying on emojis, memes and other emotional symbols to express their feelings. At the same time, the spread of machine learning and categorise of human beings is strengthening this process of us simplifying ourselves.

This project investigates how machine learning systems reduce facial expressions into discrete categories, and how this process can be revealed through a tangible, machine-mediated installation.

By using a practice-led and autoethnographic approach, the project involves building a real-time facial expression detection and photo printing pipeline to observe how human emotion is transformed into computational signals.

The system employs an OpenMV CAM for photo taking and emotion recognition, an Arduino Mega as controller and three thermal printers to materialise machine-assigned emotional labels as coloured bitmap traces, accompanied by a fan output to strengthen the visible outcome.

The research exposes the simplification, distortion and information loss which are invisible in computational emotion categorisation, making the hidden pipeline of emoji-fication visible as a continuous chain from expression to signal to physical form.

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1. Introduction

1.1 Background

Do people really laugh when they are typing an "😄" or "hhh"? Facial expressions, along with the digitalisation of the world, have always been what we human beings try to translate into something to share on the internet. The early creation of emojis was shaped by the daily emotions of that generation, while the youngest, born into internet use, somehow "learned" emotions through memes and emojis. In some ways, in the digital age, sending an emoji becomes part of our expression of feelings, alongside the natural expression of our faces. However, with these "samples" and "translations" in the digital world, would our facial expressions, or even emotions, be simplified? As noted by Danesi (2016), emojis operate as simplified affective symbols that compress complex emotional states into easily recognisable icons.

With the increasing automation of everyday systems, we not only simplify and categorise ourselves, but also enable machines and computational processes to simplify and categorise us - beyond human communication, computational systems also participate in the simplification of facial expressions. Machine-vision models do not interpret human emotions; instead, they reduce facial movements to measurable patterns that can be classified into discrete categories such as "happy", "sad", or "angry". Early algorithms, from Viola and Jones' (2001) face-detection cascade to contemporary lightweight classifiers used in embedded boards, rely on fixed features and thresholds to determine these categories. While effective for recognition tasks, such systems inevitably compress the fluid and context-dependent nature of human expression into a limited symbolic vocabulary.

With these otherwise invisible simplifications in our behaviour of relying on digital resources to express ourselves, and machine categorisation in the modernisation process, we, in effect, externalise the process of our brain transforming a feeling or expression into our facial movements in a much simpler way, which tends to obscure the fragile and individual parts of our feelings. For my practice in making this tangible interaction installation, I would like to bring those invisible processes to a physical showcase of how we re-interpret ourselves.

1.2 Research Aim & Research Question

This project aims to explore the emoji-fication and machine-mediated re-interpretation of facial input by building a tangible machine system that recognises and translates human facial expressions into signals into tangible printing and mechanical outputs, making visible an otherwise hidden emotion-to-material pipeline.

Research Question

How can facial expression signals be translated into tangible mechanical and printed outputs to explore the process of emoji-fication in a machine-mediated system?

2. Related Work

2.1 Facial Expression Recognition

Facial expression recognition systems generally follow a pipeline of detection, feature extraction and classification, operating as pattern-recognition mechanisms rather than interpreters of emotional meaning. Foundational work such as the Viola–Jones detector (Viola and Jones, 2001) established the treatment of the face as a measurable object, while later approaches like Kazemi and Sullivan's (2014) landmark alignment reinforced the emphasis on geometric patterns over affective interpretation.

Most contemporary models rely on Ekman's (1999) basic-emotion framework, which reduces expressive complexity to a small number of discrete categories. Although effective for computational tasks, such categorical systems inevitably compress the fluid, ambiguous and individually variable nature of human emotion into symbolic labels and confidence scores. This classification-based reduction remains a central limitation of machine-mediated facial expression processing.

2.2 Tangible Interaction & Materialisation

Tangible interaction research explores how digital processes can be made perceivable through physical form and action. Ishii and Ullmer's seminal *Tangible Bits* framework (1997) argues that computation becomes more understandable when its internal states are materialised in the physical world. Subsequent work has emphasised the value of representing digital information through objects, movement or spatial change, allowing users to engage with computation in embodied and sensory ways.

Within this perspective, making invisible algorithmic operations experientially accessible provides a means to expose and reflect on the mechanisms underlying computational systems.

2.3 Emoji-fication & Symbolic Compression

The rise of emoji has introduced a highly compressed visual vocabulary for expressing emotion in digital communication. As Danesi (2016) argues, emoji function as simplified affective symbols that substitute for the nuance of facial expression. Scholars have noted that such symbolic systems reduce emotional complexity into easily recognisable, standardised units, enabling efficient communication while limiting expressive depth. This form of symbolic compression parallels the categorical logic of computational systems, in which continuous expressions are translated into discrete labels. Considering emoji-fication as both a cultural and computational phenomenon highlights how emotional meaning is repeatedly reshaped through processes of abstraction and reduction.

3. Methodology

3.1 Practice-led Research

This project mainly adopts a practice-led research approach, exploring the process of emoji-fication through the act of designing and constructing the tangible system. Instead of seeking to prove a theory of emotion in digital systems, the project investigates the invisible process through which computational systems transform and categorise facial expressions into machine-readable signals. By engaging directly with a machine learning component, such as the OpenMV recognition module, and its data transfer to Arduino-driven thermal printers and mechanical outputs, the project visualises emoji-fication and machine-mediated interpretation, allowing understanding to emerge from practice rather than abstract theories.

3.2 Autoethnography & Small-scale Observation

During the development of the system, autoethnographic reflection was combined with small-scale observations to examine how machine categorisation diverges from lived emotional experience. Early false detections, such as the system producing expression scores even without a detected face, together with misclassifications and interruptions in the communication between OpenMV and Arduino, were noted as part of the system's behaviour. A small-scale user testing further exposed inconsistencies between users' actual expressions and the system's categorical outputs. Together, these observations reveal how computational processes compress and distort emotional information, offering insight into the gap between machine-readable expression and human affective nuance.

3.3 System Overview

The tangible system aims to reveal how machines detect, recognise and categorise facial signals by making each stage of this translation process visible. It combines a camera-based facial input component, a computational stage in which expressions are transformed into categorical data and bitmap photos, and a thermal printer that materialises this compressed emotional information as bitmap traces. A fan provides an additional embodied output, extending the system's classification into a physical and sensory response.

4. System Architecture & Design Intent

4.1 Facial Input & Computational Processing (OpenMV)

For the facial input system, the requirements included a camera capable of real-time detection, a facial-expression recognition module and an appropriate processing unit. A decision had to be made between building a new system using a standard camera with a Raspberry Pi or adopting the existing OpenMV Cam. Because the OpenMV Cam provides a compact camera module with an integrated microprocessor, together with a cloud-based AI training platform and built-in example scripts for face detection, the project uses OpenMV as both the image-input device and the image-processing pipeline. This configuration appropriately reflects the machine-reading logic of contemporary digital emotion-detection systems. Since the system does not require high recognition accuracy, the inherent inaccuracies of a lightweight embedded model were considered acceptable.

The facial-expression categorisation module was trained using the FER2013 dataset from Kaggle. About 500 images from the selected emotion classes (happy, surprised, sad, fear, angry) were put into training of the small-scale classifier through the official cloud AI training platform provided by OpenMV. To reduce dataset bias, brought by the fact that most FER2013 images are of European and

African people, additional photographs, about 10 for each class, were collected under the same recognition light environment and put into the dataset to diversify the training set.

4.2 Categorical Output & Tangible Differences (Arduino-controlled Printers)

For the output part, the project uses 3 thermal printers with paper of different materials layers, so that the printed contents would be in different colours: yellow for happy and surprised, blue for sad and green for fear and anger. For the reason that OpenMV has only one group of serial input and output (rx/tx) IO pins, the Arduino Mega Pro, which has 4 groups of serial pins, was chosen to be the driver of output devices. By delivering different emotion categories in different colours, the simplification of how a machine deals with an emotion case was visualised, for the audience to feel the missing of detail in emotion. And by printing in the form of thermal printers, which treat pictures as bitmap artefacts, the audience could directly feel the simplicity of emotion “signals”.

4.3 Embodied Reinforcement & Sensory Output (Fan Activation)

At the same spot that Arduino received the emotion and bitmap data, and allocates it to one of the printers to start printing, the fan at the bottom of the installation would begin operating for 30 seconds, so that the printed out comes would flutter slightly in the air, to bring a feeling of detailed emotions being blown away in the categorisations.

At the beginning, I planned to design an auto-cutting system to cut off every single outcome of a facial expression spot to be blown away physically in the air, but during the thermal printer test, I found that the long tips of the same colour stayed on it with different emotions, scores and bitmaps could actually bring a better visual expression of how machine treat abundant different emotions in a same way.

4.4 Integrated System Logic

By combining the input, classification and output parts together, the system forms a complete pipeline that turns a human facial expression into a series of simplified “signals” and physical reactions. The OpenMV module reads and categorises the face, the Arduino allocates the emotion data to one of the three printers, and the printed bitmap appears in different colours. At the same time, the fan enhances the output by bringing the printed results into a slight movement in the air.

Through this set of actions, the whole installation shows how a machine treats facial expressions in a fixed and simplified process, where different emotions are handled in the same way and translated into similar forms of material outcomes. The integrated behaviour of the system transforms emotion to signal and then to physical output, visible as one continuous chain.

5. Implementation

The implementation of the project includes supporting frame structures of 3D printed brackets and linear shafts, electronic circuit design and soldering, and software development of the OpenMV module and the Arduino controller.

5.1 Hardware Assembly & Physical Structure

To run the emotion classification module in real time, the OpenMV CAM 7 Plus was chosen to be the camera and image processing hardware. It has enough built-in memory to run face detection, emotion classification and process the photo into a bitmap at a reliable speed. In consideration of driving 3 thermal printers and communicating with OpenMV, the Arduino Mega 2560 Pro, which has 4 groups of rx/tx IO pins for serial output, was decided to be the operating board. Please see below the connection for data exchanges and printer control:

Table1. Communication of OpenMV and Arduino

Component	Arduino Pin	OpenMV Pin	Notes
Arduino → Open MV	TX0	RX (P0)	For Arduino, sending "S" & OpenMV, receiving "S" to start a loop
Open MV → Arduino	RX0	TX (P1)	For Arduino to receive the data to print of emotion, score and photo bitmap
GND	GND	GND	Share ground at LM2596 5V OUT-

Table2. Arduino to Thermal Printers and Fan Relay

Printers	Arduino Pin	Printer Pin	Notes
Printer 1 (yellow)	TX1 (D19)	RX	Prints happy/surprise
Printer 2 (blue)	TX1 (D17)	RX	Prints sad
Printer 3 (green)	TX1 (D15)	RX	Prints fear/anger
Fan	D9	Relay IN	Outputs HIGH for 30s at each print

To run the hardware in a healthy power supply system, I chose an adapter to convert AC power into 9V DC to power the thermal printers and fans, and for Arduino and OpenMV, I used LM2596 to decrease 9V to 5V. Additionally, I used a relay module for switching the fans on and off. Please see below the power and communication connections:

Table 3. Power Supply Connections

Component	From	To	Notes
Thermal printers (×3)	9V adapter (V+)	Printer VIN	Each printer has 9V independently
Fans (×4)	9V adapter (V+)	Fan VIN	Parallel connection
	9V adapter (V-)	Relay COM	Relay switches fan power on/off
Arduino Mega / OpenMV	LM2596 OUT+	5V/VIN Pin	LM2596 steps down 9V → 5V
GND	GND	GND	Share Ground at 9V

The overall structural frame was made by 10 300×12mm linear shafts, 8 500×12mm linear shafts and 4 1600×20mm linear shafts for it to have a "computational look", and the holders of Electronic components and thermal printers are designed in SolidWorks and 3D printed. To separate the thermal printed papers and the fans at the bottom, an iron net was fixed at 5 cm above the fan, and to restrict the airflow, 2 transparent PVC boards were held at the front and back sides of the printing area.

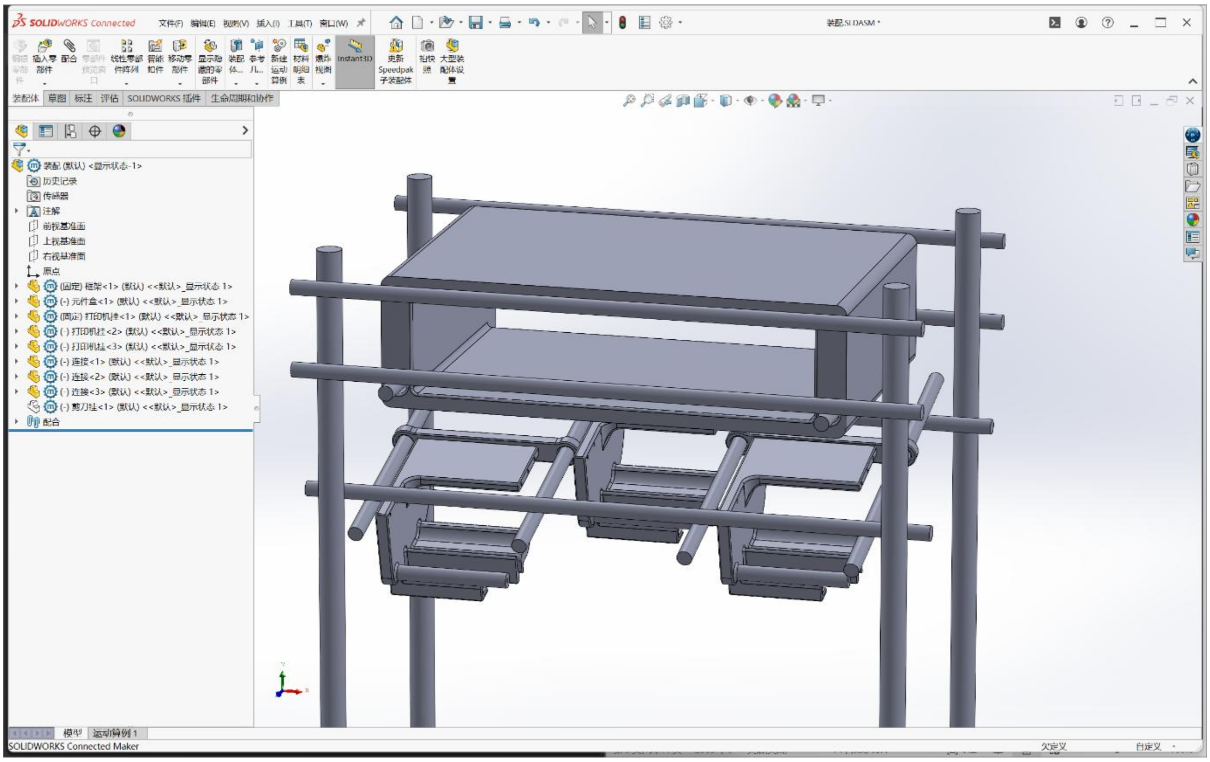

Figure 1: 3D Design of the frame and supporting brackets before material purchase and 3D printing

5.2 Software Development & System Integration

The software development mainly concentrates on the training of the facial expression classification module and the connection between OpenMV and Arduino.

The first emotion module version was trained with Python and Keras, which turned out to be too large for the OpenMV RAM to operate. After some failing attempts, I turned the direction to train a small-scale module on the official website of OpenMV.

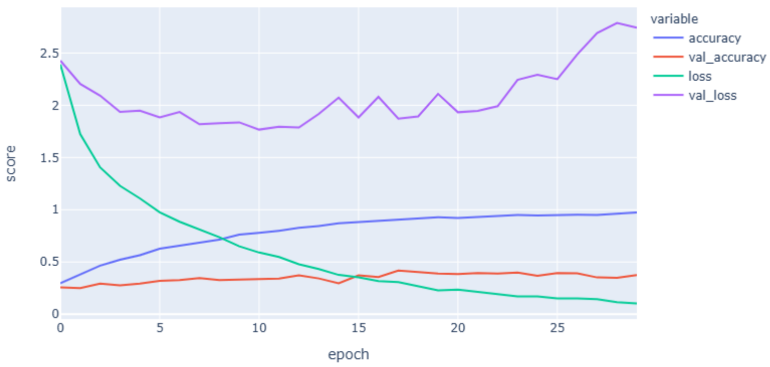

Figure 2: The model trained on https://ai.singtown.com

The first version of OpenMV facial expression certification turned out to give an emotion outcome and score when there was no face at all in the camera, so I then added a face detection logic to trigger the emotion classification after finding a face.

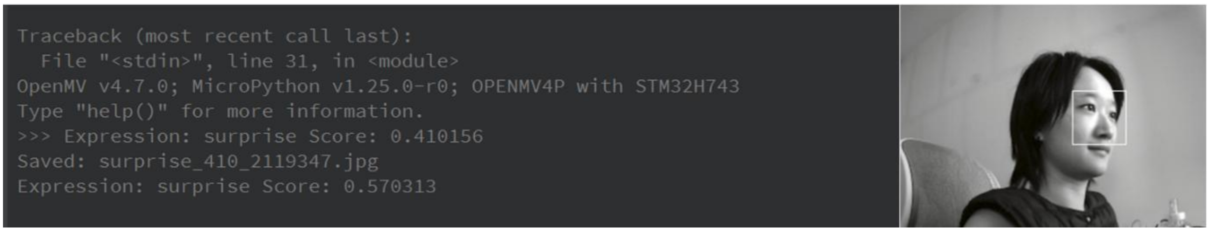

Figure 3: OpenMV succeeded in face detection and emotion classification

For the OpenMV and Arduino communication, I first tried a 2-step handshake protocol: Arduino sent "start next loop" to OpenMV to start face detection and sent emotion information, then Arduino sent "start img" for OpenMV to send the bitmap, finally, after printing, Arduino sent "start next loop" again. However, during the test, I found that the OpenMV would receive the serial information from the Arduino letter by letter at the beginning of the serial exchange, which means the two handshakes would never happen, and always miss each other, leading to the system freezing. To avoid these problems, I decided to let Arduino single-directionally control OpenMV and the printers by sending an "S" to OpenMV to start the next loop of face detection, emotion classification and bitmap sending, then aligned the suitable printer to start printing, and switched on the fan.

5.3 User Testing & Iterative Refinement

After installing all parts of the project, I went on to a small-scale user test, inviting 3 of my friends to try the whole process. The system runs once it is connected to the power supply. OpenMV and Arduino would automatically run the code inside.

6. Evaluation

The evaluation of the system was in 3 steps: printing attempts, long-time operation and user test. I tried different facial movements to successfully get printed outcomes from the 3 printers, and the emotion tags for each printer aligned with the setting, which means the system succeeded ffrom the operation aspect. Then, I keep the machine open for 2 hours, and went in front of it occationally to test if it could run in long term and whether the face detect logic succeeded. The outcome is that, the machine would wait until a person went into the camera sight and was detected, and every time Arduino would receive the right data for the printer to work. Finally, I invited my friends to try print their emotions, and they all succeed triggering the printer movement.

Figure 4: User test

There did exist a problem that fear and anger are hard to detect, which could be found in the result that the green paper is the shortest. But from the project view, this little problem has an ideal meaning that the machine would kind of miss what we are trying to express.

7. Discussion

There was an interesting thing during the printer tests. When I first wrote the Arduino code to control the thermal printer, I was using a baud rate of 115200 because I wanted the print speed could be faster. However, it turned out that the printers only accept 9600; otherwise, they would print out lines of nonsensical characters. And after the adjustment, the garbled characters and the right emotion information and photo were on the same paper, which kind of reflected the process of machine learning about people.

Overall, the project demonstrates how machine-mediated emotion processing inevitably compresses and distorts human affect. Following Ekman's (1999) categorical model, the system reduces expressions to fixed labels, making misclassifications such as confusion between fear and anger unsurprising. These mismatches are not merely technical faults but reflect the pattern-recognition logic described by Viola and Jones (2001), in which machines respond to measurable features rather than emotional meaning. The printed bitmaps and uneven paper lengths materialise this loss of nuance, echoing Danesi's (2016) argument that emoji-like symbols flatten affective complexity. By revealing these transformations, the installation highlights the persistent gap between lived emotional experience and the simplified forms produced through computational categorisation.

8. Conclusion & Future Work

As a conclusion, the project completed a pipeline from a facial expression image input to a printed outcome. The whole system route included real-time face detection, facial expression classification, transformation of photos to bitmap signals, and a tangible printed outcome. The audience could interact with the installation to experience a visualised process of how a machine would simply and categorise human emotions. It successfully brought the invisible process to a visible one.

For the next generation of this project, I am considering bringing it to a live-stream website, where visitors can see the real-time view in front of the installation. The visitors could send emojis, memes or other emoticon symbols online for the system to read and print their emotion and score, or use their own webcam to capture their own face for the machine. It needs further planning and research for the website user experience journey and legal regulations of publishing and collecting visitors' data online. By bringing it online, I am expecting it to be publicly accessible, for visitors to explore how their emotions and expressions move from facial movements to digital signals in today's internet world.

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