

# Facial emotion recognition with a reduced feature set for video game and metaverse avatars

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This paper presents a novel real-time facial feature extraction algorithm, producing a small feature set, suitable for implementing emotion recognition with online game and metaverse avatars. The algorithm aims to reduce data transmission and storage requirements, hurdles in the adoption of emotion recognition in these mediums. The early results presented show a facial emotion recognition accuracy of up to 92% on one benchmark dataset, with an overall accuracy of 77.2% across a wide range of datasets, demonstrating the early promise of the research.

**KEYWORDS**

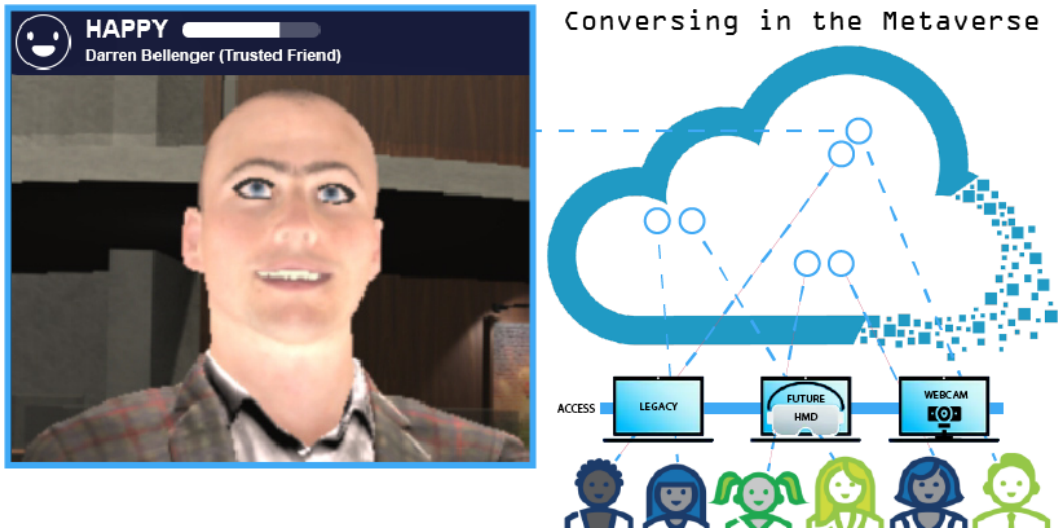
emotion recognition, metaverse, virtual reality, online games

## 1 | INTRODUCTION

As a society, we increasingly live our lives within online mediums, a prime example being the growing popularity of online games and metaverse platforms [1]. Future metaverses may eventually integrate into all aspects of our lives, from avatars embodying our physical appearance or how we want to be perceived to look, to ownership of virtual assets and currency [2]. Dionisio et al. [3], Hughes [4] define the metaverse as a "network of 3D virtual worlds focused on social connection". For this paper the term will also be used to encompass other types of virtual worlds [5].

This paper presents a novel method of integrating facial emotion recognition into metaverse platforms. This utilises facial data already held within modern 3d avatars [6], thus allowing emotion recognition to be implemented within metaverse platforms reaching a global audience. Whilst implementing emotion recognition within online mediums raises ethical concerns [7], there are many benefits to people's lives, gained from the use of this technology.

The method is illustrated in the example shown in Figure 1. Here users are conversing in a metaverse, embodied within personalised 3d avatars. Four users have access to hardware that allows for facial expressions to be visualised onto their avatars, functionality already available in some online games [8, 9]. The hardware for achieving facial capture could be either an inexpensive webcam [10], or via the facial capture technology on next generation Virtual Reality (VR) headsets (HMDs) [11, 12, 13, 14].



**FIGURE 1** An example scenario using the method where a large number of users are online

With this novel method users could be offered an onscreen indicator of the emotion others are exhibiting, gained from real-time avatar data, without adversely affecting metaverse performance. With some metaverses hosting tens of thousands of concurrent users [15], visualising and then storing facial avatar data, could realise many use cases, discussed in the next section. The proposal contrasts with existing examples of metaverse-based emotion recognition, where prediction is limited to the local personal computer setup the user is accessing [16, 17, 18]. Along with this, these examples only involve a single user accessing a metaverse, there being no attempt at scaling these solutions. The problem of scalability is an issue this proposal addresses, thus solving a barrier to the adoption of emotion recognition within games and metaverses.

## 2 | THE CASE FOR EMOTION WITHIN GAMES AND THE METAVERSE

There are compelling use cases for integrating emotion recognition within online games and metaverses, including:

- **Evolution of games.** Research has covered the capacity for using emotion within games to increase addictiveness, help create online connections and relationships [19, 20]. Games could reward positive emotional interaction [21] or reduce difficulty if a player shows anxiety. Additionally role-playing games could adjust depending on a players current emotion [22], or more helpful advice and support provided during "exer-games" [23]. Additionally game

environments could be automatically moderated for any online abuse [24].

- **Wellness technologies.** Utilising emotion within a metaverse may help improve emotion recognition in children, particularly those with autism, compared with traditional methods [25, 26, 27], and building on early VR research [28, 29, 30]. The author is researching the design of a metaverse based aid, termed EMPACT-VR, to help people recognise emotions in others. This could lead to improvements in the future care of people with an emotion recognition deficit, creating a more inclusive and equitable metaverse [31]. Such an aid could alleviate the issues these people face in everyday work and life, where a lack of social skills do hinder future careers [32, 33].
- **Improved training simulations.** Real-time tracking of learner emotion may allow for later analysis of individual or group stress levels [34]. Military training, with its increased use of simulating behaviours [35], could make use of emotion recognition to improve soldiers responses to cultural awareness and body language [36]. Referring back to the use of EMPACT-VR, using an emotional aid over a protracted period of time, may result in users learning and improving their own recognition ability. Thus game playing and spending time in the metaverse could be a subliminal learning mechanism for improving the lives of some who suffer from a reduced capacity to recognise emotions [37].
- **Opinion mining.** Customer's attitude to products could be tracked and analysed (sentiment analysis), either during online games advertising, or consumer sales with the metaverse [38, 39]. A retail metaverse may allow brands to holistically monitor their emotional connection with consumers [40] or even help brand loyalty and exclusive brand allegiance [41].

The researcher's main driver in integrating emotion recognition into a metaverse, is to improve its usefulness as an educational environment. In particular for people with emotion recognition difficulties, such as autism. The educational benefits of metaverses are already wide-scale [42], from improving trust within teams [43], to acting as a social leveller [44] and a social experimentation platform [45]. Students are now being noted to see no separation between playing and learning [43]. Earlier research has looked at improving social skills [28] and emotion recognition [29], yet without using real-time emotion recognition. In relation to the general use of metaverses within healthcare it can lower costs and allow for experiential learning [46]. The researcher intends on investigating the effects of metaverse based emotion recognition on teenage children (13-19), who currently enjoy online games and metaverses from home [47]. These will invariably be on the autistic spectrum, given autistic teenagers are known to be heavy users of online games and metaverses [48], being shown to enjoy them [30].

The proposal can currently be used with inexpensive webcams as input [10, 49]. This can help in the promotion of metaverse based education in areas of deprivation [50, 51, 52]. New metaverse platforms are already allowing users to use a variety of access methods, from expensive HMDs to lower cost effective methods [53, 54].

In attempting to improve education for people with emotion recognition difficulties, there are specific medical issues, exhibited in everyday life, that this proposal may alleviate. A lack of social skills can hinder future careers in the workplace [32, 33]. Emotional Intelligence (EI) is affected, which is increasingly important in business, given its transferability [55, 56]. Careers that require reading and responding to emotion [57] may be affected, as well as the ability to raise one's own self-esteem [58]. People may even be viewed as impersonal [59] if they lack positive reactions in meetings [60]. Those with emotion recognition deficit may struggle to sustain conversations [61], or maintain an

attention span [56].

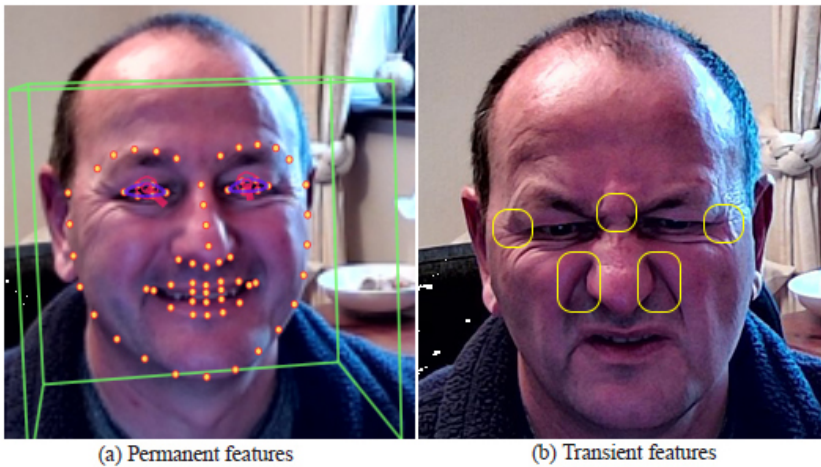
The proposed algorithm allows for emotion recognition using facial avatar data, this may realise a number of benefits:

- Recognition could take place at any point in a metaverse or game, either on a single individual or group. Large-scale group emotional analysis may then be possible with potentially no major performance hit. This raises the opportunity for emotion recognition to be used by metaverse-based digital twins or other applications.
- It would not be required to pass emotional data via a mark-up language such as EmotionML [62], Perception Markup Language (PML) [63], or Extensible Multimodal Annotation (EMMA) [64]. This algorithm may therefore result in the use of emotion recognition being more secure, as the emotional data would not be contained in human readable XML-schema.
- The method may suit new advances in VR HMDs, designed to provide facial input into the metaverses [11]. The Oculus Half-Dome research project is one such example of a new design of HMD that incorporates sensors that provide data on the changing facial expressions of a user [12]. This data is reduced from that provided by a human image, and is aimed at providing the minimum data required to accurately visualise an avatar's face [65].
- With future advances in the ability to visualise hand and body movement in the metaverse, this algorithm could be part of future multi-modal recognition. There may even be the possibility of also integrating this with EEG and ECG biosensor input [66, 67].
- Other advances in online technologies may also adopt the proposed algorithm. Nvidia have researched a replacement for traditional video conferencing, where high-quality avatars of people are animated using facial landmark data generated from a webcam [68, 69, 70]. This technology could benefit from this proposal, offering emotion prediction from this avatar data. Future Augmented Reality (AR) applications are another area where this proposal may be of benefit, due to the reduction in the amount of stored emotional data [71]. This is in part due to the lower data storage and processing power of AR devices currently [72].

One must be aware that the algorithm only utilises landmark data, therefore the accuracy obtained by this algorithm may be lower than in other research which utilise other input. This is discussed in the next section.

### 3 | RELATED WORKS

An important part of any algorithm is the input required to predict an emotion. Historically algorithms required human image-based input, from a picture, video or webcam, to predict an emotion [73]. Tian et al. [74] outline this input takes the form of landmark point data from permanent features of the face, "brows, eyes, mouth", along with optional transient features "lines and furrows, shown in Figure 2. Khadoudja and Caplier [75] note transient features indicate movement that is difficult to detect with point data, such as the wrinkling involved with negative emotions.



**FIGURE 2** Examples of data required by emotion recognition algorithms [74].

Historical research that uses permanent and transient features do claim to achieve very high accuracy levels. Liliana [76] reports an accuracy of 92.81% training a machine learning model with the CK+ dataset [77]. Stöckli et al. [78] performed a validation study of the FACET algorithm within the commercial iMotions software, reporting 96% accuracy on images, with a lower accuracy of 67% for videos. In another validation study of commercial recognition software, called FaceReader, Lewinski et al. [79] reported an accuracy of 85% validating against two datasets, ADFES and WSEFEP [80, 81].

However, these accuracy levels seem to be attained by concentrating on validating against one or two emotion dataset libraries, rather than testing on a larger range. More insight maybe gained from validation studies that review algorithms over either a larger range of libraries, or libraries that are not in popular use. Dupré et al. [82] validated 8 commercially available recognition software, with the highest accuracy found to be quite low at 61.9%. This study included reviewing both Facet and FaceReader, discussed earlier. Facet was reported to have the highest accuracy of 61.9%, with FaceReader at 57.3%. This is far below the high values cited earlier from Stöckli et al. [78] and Lewinski et al. [79]. In Dupré et al. [82], the accuracy of another commercial software called CrowdEmotion, which focuses of video recognition, had an accuracy of 48.3%.

The size of this image input data would be difficult to transmit over the internet within a game or metaverse platform. An additional difficulty is that historical algorithms perform poorly when used with images of a variety of avatars. This issue was reported by Lou et al. [83] in their research into utilising an existing algorithm to recognise the emotion of avatars. This is understandable, as historical algorithms are not designed to work with subjects as avatars, that may not exhibit transient features, or even may not be entirely humanoid in appearance.

One recent piece of new research is very similar to that proposed in this paper [84]. Siam et al. [84] created a reduced feature set using similar calculations on landmark data, to that proposed in this paper. It reports to be as accurate as 97% on one benchmark dataset with an overall accuracy of 85% across 3 datasets. The main difference with this paper is that Siam et al. [84] utilises the Google FaceMesh 468 point landmark system [85], whilst this research uses the

smaller and more commonly used Dlib 68 point system [86]. Additionally this paper's aims to show accuracy across a large range of datasets, and have a reduced feature set designed to correlate directly to the facial properties of a common metaverse avatar [6].

It is this hypothesis that predicting emotion from the facial properties of metaverse avatars, as opposed to directly via human images or webcam, will allow for the above hurdle to be overcome. Additionally this should overcome an additional issue with historical algorithms, that they perform poorly when presented with subjects as avatars [83].

## 4 | SELECTING A METHOD FOR CAPTURING FACIAL LANDMARK DATA

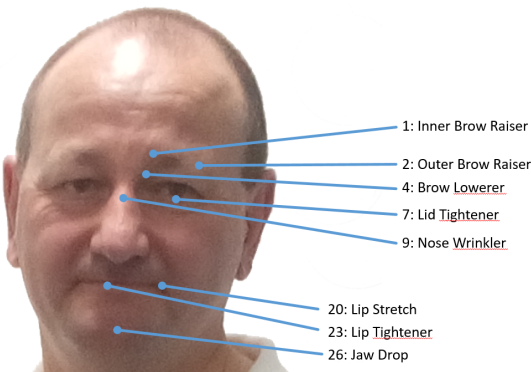
To obtain facial landmark data the research utilised the inexpensive concept of a live webcam video feed, sometimes referred to as Face Over Internet Protocol (FOIP) [8, 87]. This was due to the technology being widely available and already used, within games and metaverses for visualising avatar facial features [10, 49]. This decision eschewed newer and more expensive technologies, such as HMDs incorporating sensors [12, 88]. Additionally, it was important to select an appropriate method for detecting a face from a video image and then detect facial landmarks. As part of the research, a number of options were investigated, with a final decision made on using Dlib's shape predictor, which can be used in real-time and has been used within games [89, 10]. Dlib is a deeper learning method for detecting landmarks and is available on a wide range of devices [90], using a 68 point model for detecting landmarks [86].

The newer Google FaceMesh 468 point landmark system [85], discussed earlier, is starting to be used in research, although the researcher has not seen this used commercially as yet. This research should also be able to accommodate FaceMesh, as well as the Dlib 68 point model, given that FaceMesh incorporates the same Dlib points.

## 5 | LINKING MODERN AVATAR DATA TO EMOTION

For recognising emotions this research focuses on the Facial Action Coding System (FACS), a comprehensive anatomically based system for describing visually discernible facial movement [91]. Pioneered by Paul Ekman, FACS breaks down facial expressions into individual components of muscle movement, called Action Units (AUs). The presence of action units in a specific arrangement infers the presence of an emotion from Ekman's emotional model [92]. An advantage found with FACS is that it has been shown to generate consistent results across different ethnicities [93]. As such, the use of the Ekman emotion set, referred to in research as an emotional model [94], has become widespread. A key driver for the positional hypothesis, is that data held within current types of modern avatar, do mirror Ekman's action units (see Figure 3). This leads to the question of whether, if this facial data is already being held (to visualise an avatar's face in real-time) and transmitted over the internet, whether that data can be used for predicting emotion.

Avatar technology has evolved over the past decade, and many avatars used within games and metaverses, embody data settings to change the facial appearance in finite detail. Different terms are used for these settings, such as "bone positions" or "blend shapes", dependant on the technology platform. The second of these, is the term used for one



**FIGURE 3** Examples of Ekman action units most relevant to facial emotion recognition.

modern avatar system available for use within the popular Unity3D platform. The UMA Avatar System is a popular system used by Unity3D developers and Figure 4 shows how it links very closely to Ekman action units [6].

The concept of mapping action units onto an avatar is not new. The FACSvatar project recognises action units in real-time from a webcam and maps these onto an avatar [95]. But it is somewhat cumbersome and quite slow and has not, as yet, been integrated into a metaverse or game. FACSvatar also does not go as far as recognising and recording emotion. Other research projects have also looked at using emotion within a metaverse, but these do not attempt to predict an emotion from avatar data, but directly from webcam input [96].

## 6 | PROPOSED REDUCED FEATURE SET AND FEATURE EXTRACTOR

The proposed feature set will be based around a minimal set of 11 Ekman action units values for facial emotion recognition. These are namely action units 1/2/4/6/7/9/15/20/23/25/26 which relate to values used when controlling modern avatar facial features, see Figure 4.

The feature extractor will have two main purposes. During design its first purpose is to calculate action unit values from the images contained in the data sets, these values then being used to train a machine learning model to predict emotion. This model can then incorporated within a metaverse, where the second purpose of the feature extractor is to generate action unit values (currently via input from the webcam) to generate avatar facial settings visualising facial emotion. At this point within the metaverse, these values can then be used as input to the machine learning model, to predict the current emotional state of the avatar. This two purposes are illustrated Figure 5.

Whilst an existing feature extractor algorithm could be used to generate action unit values, the most consistently accurate of these use transient features [97]. As such, they may not be an appropriate method of generating our proposed reduced set of action unit values. Therefore this research attempts to use a simple set of calculations to make up a feature extraction algorithm. These calculations surface an approximate strength for each action unit.

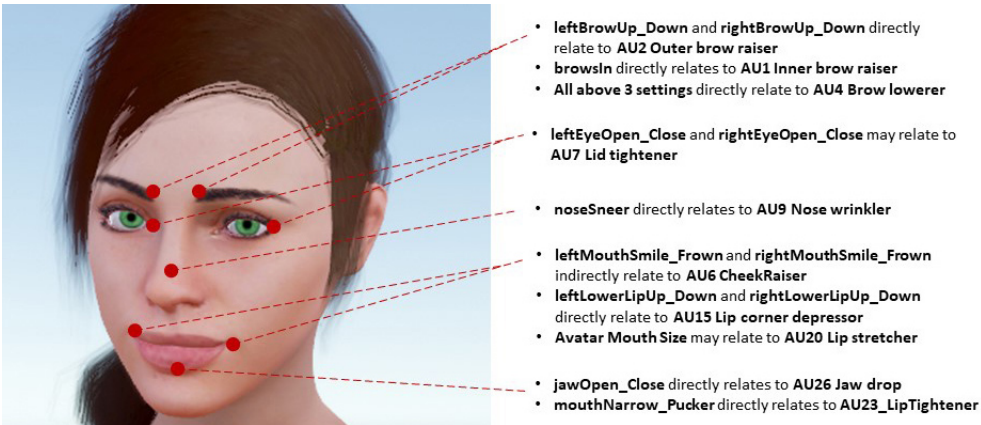


FIGURE 4 Mapping UMA Avatar System to relevant Ekman action units

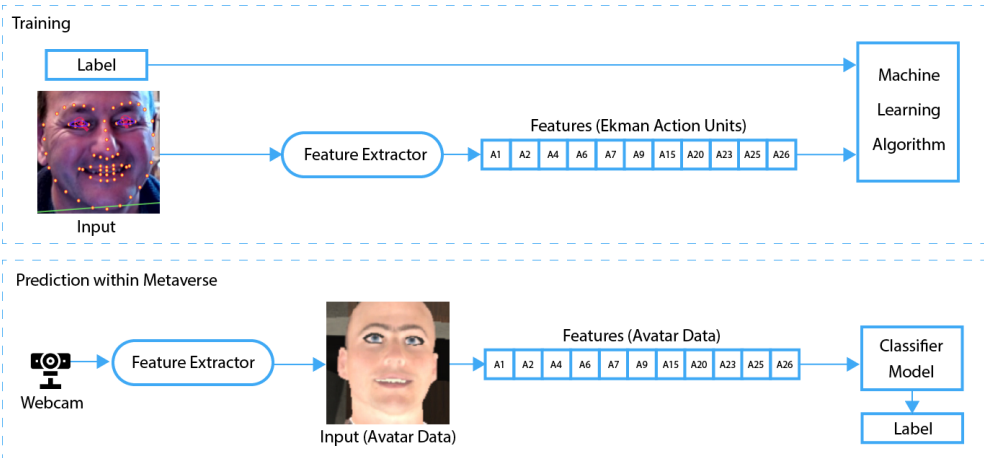


FIGURE 5 Use of the feature extractor in training and then prediction within a metaverse

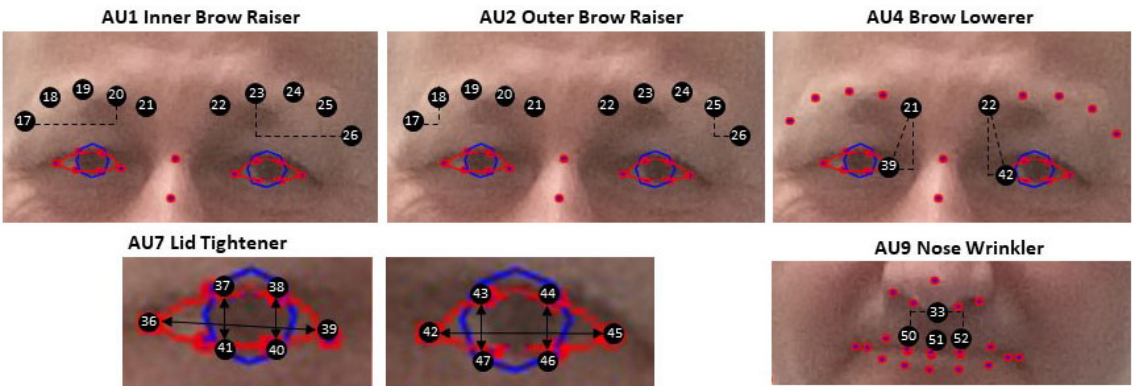
Initial draft calculations are outlined below, utilising the 68 point landmark model [86]. In making the decision to design a simpler set of calculations, research was undertaken into other algorithms that predicted emotion without using transient features. But a number were found to either not to predict in real-time, or be based on having an initial neutral image of a subject as a reference point [98, 99].

### 6.1 | Brow, eye and nasal action units

The main brow action units (1, 2 and 4) are heavily involved in predicting 5 of the 6 Ekman emotions, namely anger, disgust, fear, sadness and surprise. Along with these, action unit 7 is also involved in predicting anger. The calculations are outlined below, and based on landmarks shown in Figure 6. A number of the calculations heavily use the ATAN2 function, which is the arctangent of two numbers [100].



AU Calculation	Summary
$AU1 = \text{atan2}(y^{17} - y^{20}, x^{20} - x^{17}) + \text{atan2}(y^{26} - y^{23}, x^{26} - x^{23})$	<b>Inner Brow Raiser</b> The ATAN2 of points 17-20 and 23-26 are used together.
$AU2 = \text{atan2}(y^{17} - y^{18}, x^{18} - x^{17}) + \text{atan2}(y^{26} - y^{25}, x^{26} - x^{25})$	<b>Outer Brow Raiser</b> The ATAN2 of points 17-18 and 25-26 are used together.
$AU4 = \text{atan2}(y^{39} - y^{21}, x^{21} - x^{39}) + \text{atan2}(y^{42} - y^{22}, x^{42} - x^{22})$	<b>Brow Lowerer</b> The ATAN2 of points 21-39 and 22-42 are used together.
$AU7 = \frac{d(p_{48}, p_{66}) + d(p_{62}, p_{66}) + d(p_{63}, p_{65})}{2 \times d(p_{36}, p_{45})}$	<b>Eyelid Tightener</b> Whilst not hard to calculate using the same process as those above, most avatars only store the relative openness of each eye, not whether the certain part of the eyelid is tightening. Instead the average general openness of the eyes is used, based on the mouth aspect ratio function [101]. This uses eye points 36 to 47.
$AU9 = \text{atan2}(y^{50} - y^{33}, x^{33} - x^{50}) + \text{atan2}(y^{52} - y^{33}, x^{52} - x^{33})$	<b>Nose wrinkler</b> The ATAN2 of points 50-33 and 52-33 are used together. The higher the resultant value (beyond a minimum threshold) the greater the indication of nose wrinkling. It is accepted this method will be not as accurate as analysing transient features [102].
Note that the Euclidean distance calculation is also used: $Distance(d) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$	



**FIGURE 6** Landmark points used in calculating strength of action units 1 to 9.

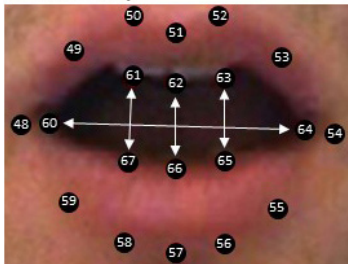
## 6.2 | Mouth, cheek and jaw action units

Action units (6, 15, 20, 23 and 26) are involved in predicting all 6 Ekman emotions. Action unit 6 is the primary indicator for happiness, with action unit 26 being a primary indicator for surprise and fear. Action unit 23 contributes towards an indication of anger, with action unit 20 contributing to fear. Finally action unit 15 is a primary indicator

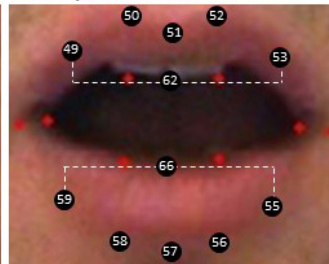
for disgust, and contributes towards sadness. The calculations are outlined below based on landmarks in Figure 7.

AU Calculation	Summary
$AU6 = \frac{d(p_{48}, p_{66}) + d(p_{66}, p_{54})}{d(p_{48}, p_{51}) + d(p_{51}, p_{54})}$	<b>Cheek Raiser</b> Mouth aspect ratio [101] is used with points 48 to 66. This produces acceptable values but needs refinement.
$AU15 = \text{atan2}(y^{48} - y^{60}, x^{60} - x^{48}) + \text{atan2}(y^{54} - y^{64}, x^{54} - x^{64})$	<b>Lip Corner Depressor</b> The ATAN2 of points 60-48 and 64-54 used together.
$AU20 = \text{atan2}(y^{59} - y^{65}, x^{65} - x^{59}) + \text{atan2}(y^{55} - y^{67}, x^{55} - x^{67}) + \text{atan2}(y^{59} - y^{66}, x^{66} - x^{59}) + \text{atan2}(y^{55} - y^{66}, x^{55} - x^{66}) + \text{atan2}(y^{59} - y^{67}, x^{67} - x^{59}) + \text{atan2}(y^{55} - y^{65}, x^{55} - x^{65})$	<b>Lip stretcher</b> The ATAN2 of points 62-49 and 62-53 are used together, with the highest value of either ATAN2 of points 59-66 plus 55-66 or points 57-59 plus 57-55. This is an acceptable indication of lip stretching but needs refinement.
$AU23 = \text{atan2}(y^{49} - y^{50}, x^{50} - x^{49}) + \text{atan2}(y^{53} - y^{52}, x^{53} - x^{52}) + \text{atan2}(y^{61} - y^{49}, x^{61} - x^{49}) + \text{atan2}(y^{63} - y^{53}, x^{63} - x^{53}) + \text{atan2}(y^{58} - y^{59}, x^{58} - x^{59}) + \text{atan2}(y^{56} - y^{55}, x^{56} - x^{55}) + \text{atan2}(y^{60} - y^{51}, x^{60} - x^{51}) + \text{atan2}(y^{64} - y^{51}, x^{64} - x^{51}) + \text{atan2}(y^{57} - y^{60}, x^{57} - x^{60}) + \text{atan2}(y^{57} - y^{64}, x^{57} - x^{64}) + \text{atan2}(y^{62} - y^{49}, x^{62} - x^{49}) + \text{atan2}(y^{62} - y^{53}, x^{62} - x^{53}) + \text{atan2}(y^{57} - y^{60}, x^{57} - x^{60}) + \text{atan2}(y^{57} - y^{64}, x^{57} - x^{64})$	<b>Lip tightener</b> In researching lip movement, a decision was taken to only evaluate the upper lip, as this has the largest differentiation in movement [103]. Therefore, the ATAN2 of the upper lip points are used together. Again this could be refined more.
$AU26 = \frac{d(p_{61}, p_{67}) + d(p_{62}, p_{66}) + d(p_{63}, p_{65})}{2 \times d(p_{36}, p_{45})}$	<b>Jaw drop</b> Using mouth aspect ratio [101] the distances between 61-67, 62-66, 63-65, are divided by 2x the distance 36-45, indicating how open the mouth appears to be.
<b>AU25 Lips Parted</b> (Boolean) is calculated. Research has pinpointed this as an additional indicator of disgust [104].	

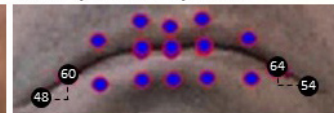
**AU26 Jaw Drop**



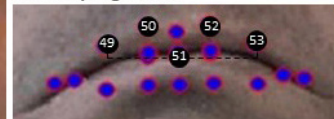
**AU20 Lip Stretcher**



**AU15 Lip Corner Depressor**



**AU23 Lip Tightener**



**FIGURE 7** Landmark points used in calculating strength of action units 6, 15 and 20 to 26.

## 7 | USING THE FEATURE EXTRACTOR TO TRAIN A MACHINE LEARNING MODEL

In the previous section we outlined the creation of a feature extractor, based around a small set of calculations. This feature extractor can now be used to train a machine learning model. With current algorithms, machine learning methods are used with facial landmarks and transient features, allowing for emotions to be classified and predicted [105]. This research followed the same methodology, initially using a support vector machine (SVM) model with the feature extractor, for predicting emotion.

Training the machine learning model requires requires a dataset library of facial images with each image annotated with the analysed emotion. A number of such image dataset libraries exist that have been extensively used in other research [77, 106, 107, 108, 80, 109, 110]. The feature extractor produces 11 action unit values (discussed in Section 6) for each dataset image, which are then linear interpolated, so that each value is on a scale between 0 and 1, reflecting the strength of each action unit [111]. The final linear interpolated values are then used as the inputs to the proposed machine learning model.

### 7.1 | Investigating the viability of integrating the model within a metaverse platform

The research initially set out to see if using the proposed design, within a metaverse platform, was viable. To facilitate this, an early draft machine learning model was trained using a moderated subset of the CK+ emotion library [77], and produced quite high early accuracy, as shown in Table 1. With the initial CK+ testing, an emotional accuracy of 73% was recorded. This accuracy was maintained when compared to a sample of Helen images [106]. The accuracy lowered for other data sets, but was still promising.

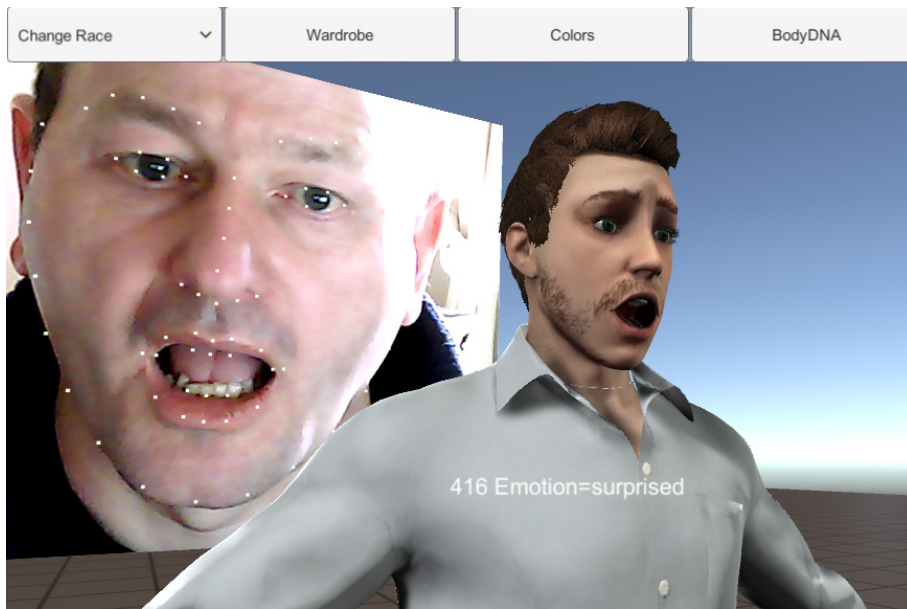
**TABLE 1** Accuracy of initial model, analysed against CK+,Helen,Yale, Jaffe, ADFES, Oulu-CASIA and FEI image libraries. [77, 106, 107, 108, 80, 109, 110]

Accuracy	CK+	Helen	Yale	Jaffe	VisGraf	ADFES	Oulu	FEI
Anger	67	50	n/a	0	31	18	29	n/a
Disgust	75	50	n/a	33	44	56	45	n/a
Fear	60	n/a	n/a	18	28	45	25	n/a
Happiness	100	76	80	41	61	100	75	67
Sadness	27	25	29	3	14	09	01	n/a
Surprise	100	60	60	91	58	86	76	n/a
Neutral	100	87	73	77	81	100	n/a	83
Overall	76	75	65	36	45	59	42	75
Overall-Neutral	73	73	62	29	39	52	42	67

As stated earlier the draft model was trained with a moderated subset of the CK+ library, later testing with other libraries was performed with full versions, with moderation only on the Helen data set [106, 107, 108, 80, 109, 110]. At this early stage, moderation of Helen data set and original CK+ was necessary, as the libraries do contain clear

ambiguous entries. This removal of ambiguity, allowed the research to also focus on refining the design of the calculations.

The machine learning model and associated feature extractor were then ready to be integrated. A prototype metaverse was developed, shown in Figure 8, which used an "every other frame" concept for emotion prediction. The metaverse was viewed on a computer setup that was based around an Intel i7-6700K processor, with 16GB Ram and an Nvidia GTX 1070 graphics card. This specification cannot be termed modern, given the processor and graphics card are quite dated. From a pure visual standpoint the metaverse was seen to not be affected by the overhead of emotion recognition, when emotion prediction was being used.



**FIGURE 8** Prototype view of facial emotion mapped onto a personalised 3d avatar

The prototype metaverse was developed using the popular Unity 3D development environment [112], which allowed for measuring the time to predict an emotion. The timings were a little disappointing with an average of 0.071 seconds, although it is the image processing that was found to take up over 95% of that time. Taking this into account, the timings show that the additional processing required for emotion prediction is a negligible burden on any game or metaverse that is already utilising facial input for avatars [8].

Whilst this test admittedly raises the question of whether integrating facial emotion prediction into a game or metaverse, where there is currently no facial input, is achievable. But given most modern webcams work at 30FPS for image capture [113], this speed opens the possibility of limiting the processing of facial input to one of every 2 to 4 frames, if one was attempting to reach the high frame rate seen in modern games [114].

## 7.2 | Improving the model by training with a diverse range of datasets

A final stage involved further improving the model by training against full versions of 6 large libraries: CK+, Jaffe, VisGraf, ADFES, Oulu and FEI. The results are shown in Table 2 with additional testing performed on the smaller Yale library. The average accuracy across the 7 libraries was 77.2%. At this point, a decision was made to move from SVM to a Multilayer Perceptron (MLP) neural network. This new approach was a large factor in the marked increase in accuracy. Another factor in the improvement was that the use of more datasets led to a more balanced training set overall, with there being less concentration of samples in any one emotion.

TABLE 2 MLP model trained on a larger set of libraries

Accuracy	CK+ (all)	Yale	Jaffe	VisGraf	ADFES	Oulu	FEI	ADFES(V)
Anger	71	n/a	37	39	68	63	n/a	45
Disgust	76	n/a	45	11	86	45	n/a	86
Fear	88	n/a	41	56	86	57	n/a	55
Happiness	96	80	68	81	100	88	92	100
Sadness	57	20	29	36	36	39	n/a	23
Surprise	100	87	73	81	90	85	n/a	77
Neutral	96	47	87	67	91	n/a	89	91
Overall	92	58	54	53	80	63	90	68
Overall-Neutral	85	62	49	50	78	63	92	64

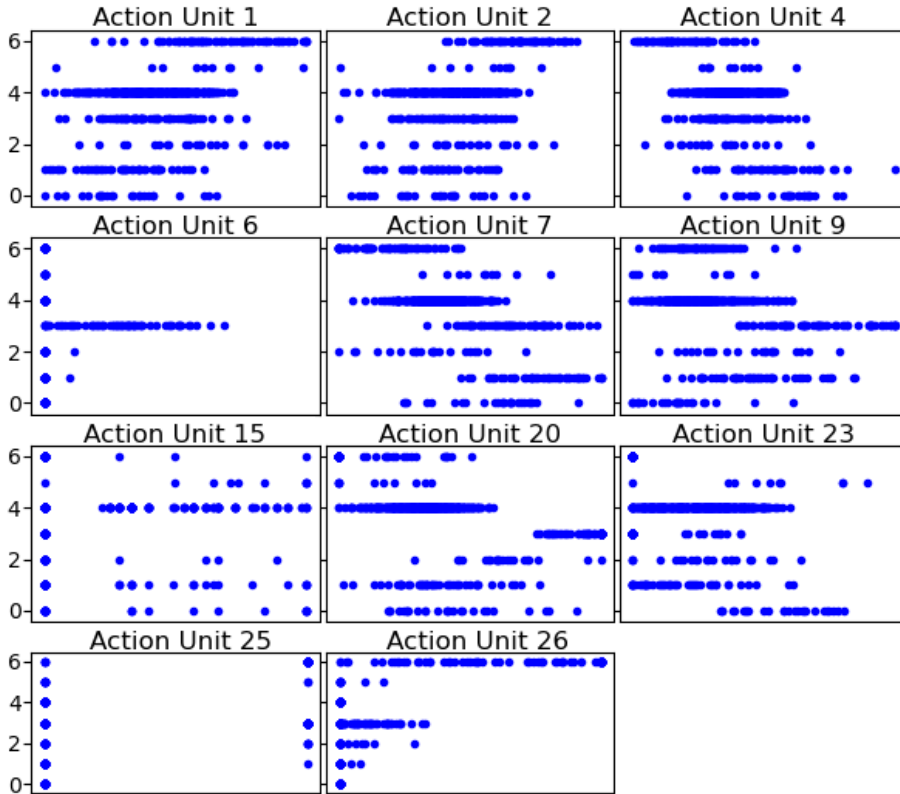
A benefit of using such a large number of dataset libraries is the increase in diversity offered. A number of libraries have a much greater amount of actors, that come from diverse cultures, not represented any single library. Jaffe was created from volunteers who were solely Japanese females, whilst Oulu-CASI contains a large amount of Chinese volunteers (both male and female). Using many dataset libraries can introduce issues though, both Jaffe and Oulu-CASI use a much smaller image size, which may have an affect on accuracy, in comparison to other libraries.

It is important to note that when analysing the ADFES video library, a threshold accuracy of over half of a videos frames needed to be correctly recognised, before a video was denoted as being correctly analysed as a whole. This threshold may seem low, but with many videos it is found that only a portion of a video shows an actor, or actress, expressing an emotion.

## 7.3 | Evaluation of the results

The final accuracy of 77.2% is higher than that found in commercial emotion recognition software from some recent validation studies [82, 78]. It is though admittedly lower than validation studies that purport to achieve over 90% [115, 76]. It must be stressed that validation studies showing very high accuracy levels, generally analyse one or two image dataset libraries, an accuracy this research could have achieved by reporting on the CK+ and FEI. A recent survey of academic research found accuracy levels can vary from 57.2% to 99.8% [116], therefore in this context, the early accuracy obtained from this research is promising.

Looking in more detail at the relative accuracies across the data sets that incorporate the full range of the Ekman emotional model, we can see that Happiness, Surprise and Neutral have the highest accuracies, with Sadness being the most inaccurate. This ordering of accuracies can be seen in other academic research [76, 77]. Currently the research results show quite a wide variance in accuracy distribution across the emotions, this is not unique though and has been found when validating commercial algorithms [78].



**FIGURE 9** Distribution charts of action unit values for the final trained model

To investigate this variance in accuracy, distribution charts for each action unit were created, shown in Figure 9. A number of observations can be made:

- **(0) Anger:** has a fairly close spread of values across the action units that indicate it (namely 1,2,4,7 and 23). Given there is no primary action unit indicator for this emotion, the value spread may not be good enough to produce a high accuracy. Additionally the wide spread of values in action unit 15 could be factor in reduced accuracy.
- **(1) Disgust:** the spread of values across action unit 15 does not seem to provide any useful demarcation that could help in identifying an emotion. As this action unit is used for indicating Disgust this may be a main reason behind the lower accuracy with this emotion. This is a shame as there is a good spread of values across other

action units, especially 1,2 and 4 which contribute indicating the emotion.

- **(2) Fear:** which embodies action Units 1,2,4, 20 and 26, does not have a clear visible demarcation in any unit, thus possibly contributing to its lower accuracy.
- **(3) Happiness:** has excellent demarcation in action unit 6 allows for a strong accuracy with this emotion. There is also some additional demarcation in action units 7,9,20 and 26 that can add to this accuracy. With the values in action unit 15 being zero, this will also contribute to the accuracy gained.
- **(4) Neutral:** shows a larger number of readings in all charts, which is due to the unbalanced nature of the training data, in favour of this emotion. Whilst no single action unit defines this emotion, one can see that it has a uniform presence in nearly all of the charts (except action unit 15), possibly leading to its high accuracy.
- **(5) Sadness:** shows a spread of values across action unit 15 that does not seem to provide any useful demarcation that could help in identifying this emotion. As this action unit is used for indicating Sadness this may be a main reason behind the lower accuracy with this emotion. Additionally the emotion has quite poor demarcation across other action units, including 1,2 and 23.
- **(6) Surprise:** the excellent demarcation in action unit 26, along with no spread in action unit 23, allows for strong accuracy. Whilst the demarcation in action unit 25 is not easily seen in the chart, it does also help accuracy. There is also a close spread of values across action units 2,4,7 and 20 which would improve accuracy further.

Including the ADFES video dataset in the analysis, allows the research to take an early look at the algorithms accuracy recognising emotion in videos. The 68% accuracy achieved analysing ADFES compares favourably with other research studies [82, 117]. This though would require further investigation, the ADFES dataset is a library of posed emotions, with other video datasets incorporating conversations. It is possibly too early to suggest whether this novel feature extraction algorithm may work as well on videos as it does on images, although the accuracy gained is promising.

## 7.4 | Future improvements

After analysing the results of the final trained model a number of recommendations can be made, for future improvements. These center on the training data, image capture and calculations, these are:

1. **Algorithm improvement.** The calculations for indicating the presence of some of the action units should be improved. In particular, action unit 15 but also action units 2 and 4 could be re-appraised.
2. **Continue increasing diversity.** Look into expanding the training data with further image dataset libraries, to increase the diversity of the model further.
3. **Improve facial landmark capture.** Whilst the Dlib method of facial landmark capture performed well. There were still some issues around chin dimpling affecting the accuracy of landmarks around the mouth. Looking at implementing ways of mitigating against this, may increase accuracy.

There is scope for improving the feature extraction algorithm along with expanding the training data. Pursuing these may allow the research to approach the accuracy purported by other research.

## 8 | CONCLUSION AND FUTURE WORK

In this paper we introduced a novel method for predicting facial emotion using a reduced feature set, designed for use with metaverse-based avatars. The machine learning was trained and then quantitatively evaluated using a range of image datasets, producing initial promising results.

Earlier in section 7.4 future improvements were identified and covered revisiting and fine tuning the calculations that make up the feature extraction algorithm, with a view to improving accuracy in an attempt to match the accuracy reported in other research. Accompanying this improvement, gaining access to more culturally diverse image datasets, for both model training and evaluation, will increase the validity of the research.

Future work may also incorporate integrating the method into an example metaverse to showcase its feasibility. Additionally a qualitative review could then be conducted to gain an early insight into the integration of emotion recognition into metaverse platforms.

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