Vol 8, No 2, 2022 Series

Emotion Recognition and Prediction Using Machine Learning

Aweh O., Parker, E-C. A. & Dagah, W.D.
Department Of Mathematical And Physical Sciences (Computer Science Programme)
Afe Babalola University
Ado-Ekiti, Nigeria.
Emails: opaniaweh@gmail.com, opaniaweh@abuad.edu.ng; alexanderparker1000@gmail.com, wdagah14@gmail.com

ABSTRACT

Sports is an activity requiring skill or physical prowess and often of a competitive nature. It is also an area which requires a lot of data analysis nowadays as Cintia and co. agreed in 2015. Analysis in sports is now used to judge sports performance using various scientific methods and techniques from different areas such as statistics, data mining, data analysis, e.t.c. The ability to recognize facial expressions of emotion is vital for effective social interaction. Facial expressions show a lot of emotions being felt by an individual and being able to recognize these expressions would help us to know how certain individuals feel and subsequently know how they interact with others. According to emotions theorist Izard (2002), the inability to recognize nonverbal forms of emotional expression can negatively affect intra-and interpersonal behaviour and may serve as a risk factor for poor adjustment and future adverse outcomes. This paper examined emotion recognition and prediction of outcomes in sports using machine

Keywords: Emotion, Emotion Recognition, Emotion Prediction, Machine Learning, Facial Expression, Facial Expression Recognition (FER).

Journal Reference Format:
Aweh O., Parker, E-C. A. & Dagah, W.D. (2022 Emotion Recognition and Prediction Using Machine Learning. Social Informatics, Business, Politics, L:aw, Environmental Sciences & Technology Journal. Vol. 8, No. 2
Pp 53-64. www.isteams/socialinformaticsjournal

1. INTRODUCTION

As we now have intelligent machines, the need to be able to recognize emotions is also rising on par. In the area of theoretical science to engineering, emotion recognition has drawn extra concentration. Emotion has a great impact on decision-making and interpersonal communication and there are a lot of difficulties in being able to detect emotions. Because the number of basic emotion labels is arguable till now (Ortony, 2004) and the same emotion can be defined in different ways depending on the situation. Another problem is that the emotion of a particular class may carry the component of other classes.

Emotions speak volumes about the state of mind of individuals. Different individuals express varying degrees of emotions in similar circumstances. And the ability to accurately determine or predict these various emotions place a significant role in being able to advise, motivate or mollify any of such individuals. Emotion Prediction is becoming an active area of study. Ordinarily, based on personality attributes or types, most persons hardly express their emotions openly or formally.

Therefore, being able to predict emotions will go a long way in helping to properly guide such individuals. For example, most students exhibit mood swings, while some ordinarily feel easily depressed based on one circumstance or the other and this can affect their academic performance. And some of these students may not bother to go for counselling on their own. Therefore, the ability to read their mood would be able to help tackle whatever the problem may be. In sports, especially football, players' emotions have been shown to play a vital role in their performance during football matches. And being able to accurately determine such sportsmen or sportswomen's emotions would enhance the performance of such players in the field of play.

2. REVIEW OF RELATED WORK

An emotion is a feeling such as happiness, love, fear, anger, or hatred, which can be caused by the situation that you are in or the people you are with. Emotion is the part of a person's character that consists of their feelings, as opposed to their thoughts. Emotions are psychological states brought on by neurophysiological changes, variously associated with thoughts, feelings, behavioural responses, and a degree of pleasure or displeasure. There is currently no scientific consensus on a definition. Emotions are often intertwined with mood, temperament, personality, disposition, or creativity. There are different types of emotions that can influence the way we live and talk to others. Sometimes, it may seem like these emotions rule us. The actions we take, the choices we make and the perceptions we have been influenced by greatly impact our emotions at any given moment. Witnessing behaviours and behavioural patterns from important figures in our lives conditions us to develop beliefs about our emotions, for many of us we may have grown up in homes where no one discussed their feelings or in a home where certain feelings were linked to being "bad" or "good". That being said, as an adult this can then lead to difficulties in understanding how to regulate your emotional experiences.

No matter what you may or may not have learned, it's important to understand your feelings and emotions, including how they manifest in your body. Five basic universally experienced in all people irrespective of their cultures. These emotions are sadness, happiness, surprise, fear and anger. If we try to go further and expand these emotions, we will come up with other emotions such as shame, pride, excitement and embarrassment. Despite vast differences in the culture around the world, humanity's DNA is 99.9% similar. There are few attributes more central and universal to the human experience than our emotions. Of course, the broad spectrum of emotions we're capable of experiencing can be difficult to articulate. That's where this brilliant visualization by the Junto Institute comes in.

This circular visualization is the latest in an ongoing attempt to neatly categorize the full range of emotions logically. Below is the visualization by the Junto Institute.

social Informatics Journal
Business, Politics, Law, Environmental Sciences & Technology
Vol 8, No 2, 2022 Series

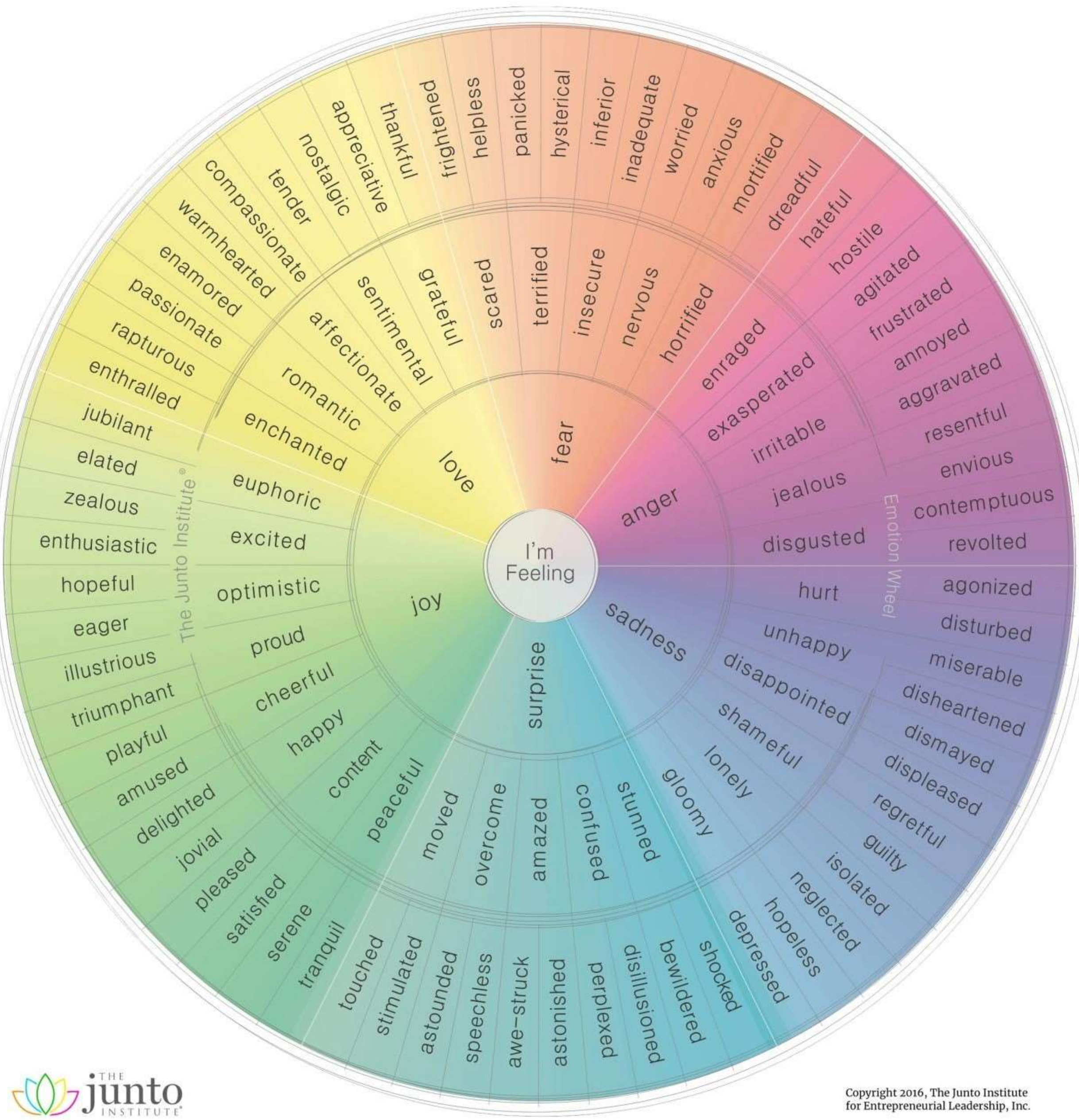

Fig 1: Junto Institute's Chart

social Informatics Journal
Business, Politics, Law, Environmental Sciences & Technology
Vol 8, No 2, 2022 Series

The concept of mapping the range of human emotions on a wheel picked up traction in the 1980s and has evolved ever since. One of these original concepts was developed by American psychologist Robert Plutchik, who mapped eight primary emotions—anger, fear, sadness, disgust, surprise, anticipation, trust, and joy. These "high survival value" emotions were believed to be the most useful in keeping our ancient ancestors al

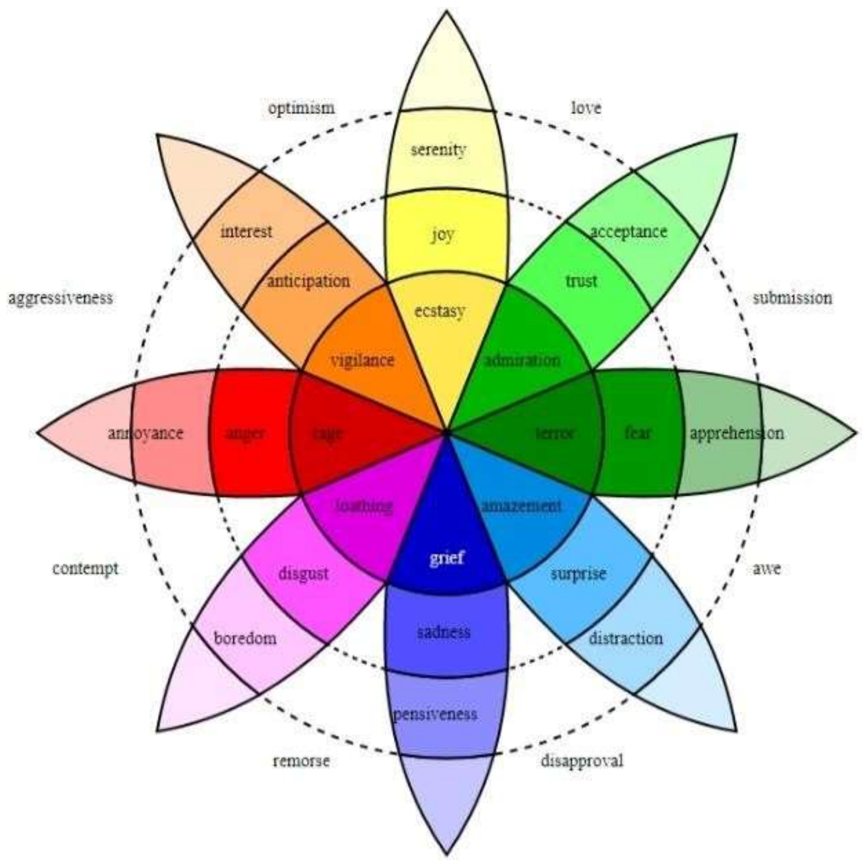

Fig 2: Plutchik Wheel

The more we research human emotion, the more nuanced our understanding becomes in terms of how we react to the world around us. Emotional intelligence is "the ability to recognise our feelings, the feelings of others, to motivate ourselves and to manage our relationships with others and ourselves appropriately". A person with great sporting qualities, without good emotional intelligence, will find it difficult to achieve optimum performance and will be surpassed by a person with lesser abilities with the opposite capabilities. Emotional intelligence is, above all, our ability to manage ourselves and others effectively. It involves connecting with our emotions, managing them, self-motivating ourselves, curbing certain impulses, and overcoming frustrations. Emotion Recognition is a technology used for analysing sentiments from different sources, such as pictures and videos. It belongs to the family of technologies often referred to as 'affective computing'; a multidisciplinary field of research on computers' capabilities to recognise and interpret human emotions and affective states and it often builds on Artificial Intelligence technologies.

Facial expressions are forms of non-verbal communication, providing hints for human emotions. For decades, decoding such emotional expressions has been researched interest in the field of psychology as mentioned by Ekman and Friesen in 2003 but also in the Human Computer Interaction field (Abdat, 2011). Many companies, ranging from tech giants such as NEC or Google to smaller ones, such as Affectiva or Eyeris invest in the technology, which shows its growing importance. There are also several EU research and innovation program Horizon2020 initiatives exploring the use of the technology FER analysis comprises three steps: face detection, facial expression detection, and facial expression classification of an emotional state.

Emotion detection is based on the analysis of facial landmark positions (e.g. end of the nose, eyebrows). Furthermore, in videos, changes in those positions are also analysed, to identify contractions in a group of facial muscles (*Koehrsen*, 2018). Depending on the algorithm, facial expressions can be classified as basic emotions (e.g. anger, disgust, fear, joy, sadness, and surprise) or compound emotions (e.g. happily sad, happily surprised, happily disgusted, sadly fearful, sadly angry, sadly surprised) (Du, 2014). In other cases, facial expressions could be linked to the physiological or mental state of mind (e.g. tiredness or boredom).

Current research and public interest in Facial emotion recognition stem from a rich history. Scientific study and understanding of emotion are thought to have begun in the 19th century with Charles Darwin's The Expression of the Emotions in Man and Animals (originally published in 1872) and G.G. Duchenne de Bologne's "The Mechanism of Human Facial Expression" (originally published in 1862) (Mayne & Bonanno, 2001). These early works focused on the important role of facial displays in emotional life and introduced the theory that emotions may be understood as biologically-based reflex behaviours serving adaptive functions. The Darwinian theory, that emotions serve to aid in survival and that facial expression and otherphysiological responses serve to communicate intentions, was firmly rooted in the view of emotions as catalysts for physiological action.

To examine this increasingly recognized topic more deeply it is fitting, to begin with, the research on how Facial emotion recognition is thought to develop in childhood and throughout the life span. As well, the role of culture, class, gender and cognitive ability in FER is important to review. Facial emotion recognition ability tends to follow a developmental path, increasing in accuracy through experiences with others and cognitive development. The ability to identify emotions from facial expressions begins in infancy, and the ability to attach labels to basic emotions begins for most children by age 18 months (Bretherton, 1981). Findings from cross- sectional studies have suggested that the recognition of certain emotions (happy, sad, and angry) improves to a near-adult level by age 5. Although the ability to distinguish more sophisticated expressions (e.g., disgust and surprise) appears to develop later, most children can identify and label the basic emotions of happiness and anger by approximately 3 years of age (Izard, 1995).

The precise mechanisms involved in the development and processes of Facial emotion recognition ability are unclear and continue to be the subjects of much research. However, there is evidence for the importance of both early childhood experiences (Gibb, 2009; Pollak, 2002) and the development of emotion processing neural systems (Herba, 2004) in the development of Facial emotion recognition abilities. How individuals process nonverbal emotional expressions and how this processing may affect social interaction and behaviour has been of increasing research interest since the 1990s (Crick, 1994; Maxim, 2003; Nowick 1992; Plesa-Skwerer, 2006; Pollak 2002). Childhood FER deficits are risk factors for ongoing relational difficulties.

As Blair (2003) summarized in a literature review on the neural communication mechanisms involved in facial expression production and recognition, Emotional expressions allow the rapid communication of valence information between individuals. They allow the observer to rapidly learn which behaviours and objects (including foods) to approach or avoid, as well as information allowing rapid modification of behaviour according to the social environment and hierarchy. Impairment in systems that respond to the emotional expressions of others can have devastating effects (p. 568). According to Blair, development may be adversely affected by inadequate response to others' emotional expressions (e.g., autism, psychopathy). Effects of Culture, Gender, Cognitive Ability and Environment Research studies examining the associations between cultural variables and FER have focused on the universality of recognition of facial displays of emotion, as well as cultural differences (Elfenbein, 2002; Ekman, 1994; Matsumoto, 2006). According to researcher Matsumoto (2006), "Whereas we all recognize universal emotions at levels well beyond chance, there are cultural influences on the absolute levels of recognition accuracy and judgments of intensity and internal subjective experience" (p. 230). Recent research on cultural differences in Facial emotion recognition suggested that children from economically disadvantaged homes may develop emotion recognition abilities later than children from more advantaged homes; such deficits were also related to social adjustment (Fine, 2001).

However, this apparent link may relate to other variables, such as parental attention and involvement and environmental stress. For example, in a sample of African-American pre-schoolers living in high-stress environments, Smith and Walden (1998) found greater accuracy for fearful expressions than was expected for this age group. They theorized that recognition of fear might have been particularly important in these high-stress environments. Thus, "the environment in which children develop may bias children towards the identification of specific expressions" (Herba & Phillips, 2004, p. 4). Facial emotion recognition appears to have a mild association with gender, with females having a slight advantage over males in some studies, and no advantage in others (Herba, Landau, Russell, Ecker, & Phillips, 2006; Lancelot & Nowicki, 1997; Steele, Steele, Croft, 2008; see Hall, 1978 and McClure, 2000 for reviews). Research findings have suggested that gender may moderate the relationship between emotion recognition abilities and social adjustment. For example, in a sample of 39 children in residential care for psychological problems (aged 9-14 years), lower Facial emotion recognition was significantly correlated with greater externalizing problems (as rated by teachers) in girls, but not in boys (Lancelot & Nowicki).

These researchers suggested that females, typically more interested in social relations than males, placed greater value on social skills. Thus, social deficits, resulting in externalizing behaviour problems, posed greater problems for females, than for males (Lancelot & Nowicki). Findings from a recent study focusing on processing speed as well as accuracy found that adult females exhibited faster- processing speed in identifying adult facial emotion expressions and that this difference was particularly apparent when identifying the negative emotions of sadness, fear, anger, and disgust (Hampson, van Anders, & Mullin, 2006). A female FER advantage was also found in a study investigating the recognition of emotion in infants' facial expressions. (Babchuk, Hames, & Thompson, 1985). Findings from the Babchuk et al. (1985) study suggested an evolutionary explanation for this female advantage. Thus, FER gender differences may relate to evolutionary development and/or social learning. Facial emotion recognition develops through childhood and adolescence, as does cognitive ability. However, these processes may develop differentially (see Herba & Phillips, 2004 for a review). Some studies have suggested a lack of relationship between FER and cognitive ability (Nowicki & Duke, 1994; Nowicki & Mitchell, 1998). The development of FER involves perceptual learning and experience with emotion. Thus, spatial attention and memory recall, as well as environmental emotion-related experiences, appear to contribute to children's ability to recognize emotions displayed in facial expressions (Pollak, Messner, Kistler, & Cohn, 2009).

3. MATERIALS AND METHODS

The Agile methodology is suggested through the processes of requirement analysis, system analysis, system design, implementation, results from analysis and testing; to evaluate the accuracy and effectiveness of our facial recognition software, as well as the relevance of adaptive decision-making using the facial expression of learners. Important system developmental tools have also been highlighted to ensure better understanding. In conducting research involving machine learning and deep learning algorithms, there is a dire need for datasets since these algorithms are driven by data. As such, careful diligence needs to be observed in the selection of the datasets for facial expression recognition, as an inappropriate selection such as datasets with noisy backgrounds might result in increasing the difficulty of the project as well as affect the overall recognition accuracy.

Facial pre-processing is the first step in facial expression recognition. Pre-processing of facial expressions is performed to discard irrelevant information and improve the recognition accuracy of the important extracted features. It involves processes such as face detection and other image modification methods such as smoothening and normalisation. Face detection is the first step in any face image analysis or facial expression classification. It is useful in determining the existence of a face in an image as well as aligning the face for the efficient extracting of the relevant features (Bhardwaj & Dixit, 2016; Martinez & Valster, 2016). After the pre-processing stage, the next step is to extract the features. Feature extraction is mostly considered the most important step in facial expression classification, as the selection of the features is an important task. It helps in representing the facial image effectively by extracting the subtle changes of a facial image into a feature vector (Abouyahya et al., 2016; Bhardwaj & Dixit, 2016).

The Local Binary Pattern (LBP) is a commonly used appearance feature extraction method due to its numerous advantages. LBP has been widely adopted because it is easy to implement, invariant to rotations, robust to grayscale transformations caused by illuminations variations, tolerance to illumination, overcomes the problems of disequilibrium displacement, possess discriminative power, uses a modest amount of data and can save computational resource whilst retaining facial information (Ojala, Pietikäinen, & Mäenpää, 2002). There are numerous machine learning and deep learning techniques employed for various applications. For our experiment, both machine learning and deep learning techniques were selected based on their performance and popularity. A brief description of the classification algorithms is as follows:

Support Vector Machine: It is the most exploitable machine learning algorithm for facial expression recognition due to its good classification accuracy; it may even gain a better classification accuracy than the neural networks (Bhardwaj & Dixit, 2016). SVM has good generalisation ability especially when the labels are properly defined, efficiently process high- dimensional feature data and is highly flexible to data size; making it a dynamic and interactive algorithm for facial expression recognition (Ekundayo & Viriri, 2019; Jakkula, 2011; Michel & El Kaliouby, 2015).

Convolutional Neural Network (CNN): CNN originally proposed by Lecun, Bottou, Bengio, & Ha (1998), is an 'end-to-end' multi-layered algorithm; an advancement of artificial neural network (ANN) (Yunxin Huang et al., 2019). It is popularly employed for image recognition purposes as well as other computer vision tasks as it requires little or no data engineering.

Ensemble Method: In predicting an outcome, the ensemble method builds numerous models byemploying either multiple different algorithms or training datasets (Kotu & Deshpande, 2015). Then the independent base models are combined using a technique such as averaging to produce a result.

Ensemble methods are normally employed in supervised machine learning tasks. Ensemble methods usually produce optimal models from the combination of multiple base models since the generalisation error is minimised, as there is the likelihood that the error of the single model will be balanced by the other base models. Also, the averaging of the multiple different models with minimum bias leads to a higher prediction performance of the model as compared to a single predicted model (Valero, 2016). Ensemble methods in machine learning are good techniques as they solve issues of overfitting and have proven to be a computational cost- effective method (Dev & Eden, 2019; Sagi & Rokach, 2018).

Choosing a machine learning programming language for this research work is always a difficult task as there exists a number of these languages. Therefore, we evaluated the pros and cons of each of the most widely used machine learning programming languages and selected one of them. These popular machine learning programming languages include Python, C/C++, Go, R and Matrix Laboratory (MATLAB) (Gao et al., 2020).

MATLAB is an interactive, easy-to-use, fast programming language that is used for scientific computing. It can be employed for tasks such as data analysis, development of algorithms, matrix manipulations, problem-solving and so on. MATLAB has good performance, provides easy-to-use graphics, and concise syntax and allows for easy language extension, however, a licence is required to use the product and some of its libraries. Go is an open-source programming language developed by Google with syntax similar to C used for building simple, efficient, and reliable software. Its syntax is concise, and expressive and enables the flexible segmented construction of programs. When implementing machine learning algorithms, libraries written in Go are used other than using other libraries in different languages. However, these machine learning libraries in Go are not numerous. R is an open-source programming language for statistical computing. R is highly graphical, producing high-quality images. Yet it is characterised by a steep learning curve and limited when analysing big data as it stores its data in the system memory (RAM). C/C++ is a powerful and efficient general-purpose programming language used across multiple platforms. However, it is difficult developing and implement machine learning algorithms using C/C++ as it is challenging to learn C/C++ (Gao et al., 2020; Valero, 2016).

After careful analysis and evaluation, python was selected as the programming language for this research as it is easy to use, requires no licence, has easy portability, well-defined error model based on exceptions, has good performance, is simple and easy to learn, efficient, availability of a documentation and community support to resolve problems within the shortest possible time (Gao et al., 2020; Oliphant, 2007; Pérez, Granger, & Hunter, 2011). The following packages and development environment were employed for this research, following the selection of python as the programming language. Familiarity, flexibility, simplicity, the availability of detailed documentation for easy implementation and community support were the reasons for the selection of these packages and development. As the success of machine learning or deep learning project is dependent on the frameworks and libraries available to developers (Valero, 2016). A brief description of them is as follows.

Anaconda

Anaconda is a complete, open-source package manager, environment manager, and Python and R programming languages distribution for scientific computing and data science. It is easy to download and install and functions on cross-platforms. It simplifies package management as well as deployment. Anaconda provides a graphical user interface (GUI) which includes a link to all the applications which can be installed with just a mouse click. The applications included in the Anaconda package include JupyterLab, JupyterNotebook, Spyder, Orange, Glue, Visual Studio Code and RStudio. It simplifies installing of libraries and dependencies as it comes with over 250 automatically

Social Informatics Business, Politics, Law, Environmental Sciences & Technology Journal

Vol 8, No 2, 2022 Series

installed packages and over 7500 open-source libraries which can be installed using either pip or conda. In addition, multiple virtual environments can be created using Anaconda. For example, a Python 2.7 can be installed instead of the default python. Also, Anaconda provides detailed documentation as well as community support for additional help (Watkins, 2018).

Open Source Computer Vision Library (OpenCV)

OpenCV is an open-source python library built for image and video analysis such as face detection and recognition, identifying objects, classification of objects in video etc. with more than 2500 optimised computer vision and machine learning algorithms. It has the interfaces: Python, C++, MATLAB and Java interfaces and functions on a cross-platform. We utilised OpenCV mainly for our pre-processing stage as it contains functions such as the Viola-Jones algorithm for face detection and image smoothening functions like a median blur () and close () for histogram equalisation. This greatly reduces the efforts required for the pre-processing stage (Culjak, Abram, Pribanic, Dzapo, & Cifrek, 2012).

Tensorflow

Tensorflow is a free, open-source library used for numeric computation. Tensorflow operates using dataflow graphs and provides an end-to-end implementation and training of machine learning models particularly neural networks. Tensorflow allows for its deployment across diverse platforms such as GPU, CPU and TPU. The higher layers provide an application programming interface (API), commonly used in deep learning models (Culjak et al., 2012).

Keras

Keras is a deep learning API written in Python for developing and training deep learning models. It is integrated into Tensorflow and was developed for faster experimentation of deep learning models. Keras has a user-friendly, highly productive interface and modulable and composable models. For this research, Keras was utilised for our data augmentation as well as the training of our deep learning models.

Table 1: Summary of the Package Development and Environments.

Operating system	Windows
Language	Python 3.9.12
Editor	Spyder (Anaconda)
Environments	OpenCV, Keras, Tensorflow

Procedures used in data collection and information gathering are here, outlined and analyzed. Data was carefully collated and objectively evaluated to define as well as ultimately provide solutions to the problems for which the research work is based. During the research work, data collection was carried out in perusals through downloads of player images and videos from relevant websites e.g. YouTube, and other research materials increased my knowledge and aided my comprehension of diagnostic processes. Facial emotion recognition is the process of finding the human face from the image and, if present, returning its location of it. It is a special case of object detection. Objects can be anything present in the image including human and non-human things like trees, buildings, cars and chairs. But, other than a human being itself objects are least likely utilized in advanced applications. So, finding and locating the human face in the image is an interesting and important application of modern times. However, locating the face is not an easy task in the image since images do not contain only faces but other objects too.

Moreover, some of the scenes are very complex and filtering out the unwanted information remains a tough task. When the presence and the location of the face are found then this information is utilized to implement more sophisticated applications such as recognition and video surveillance implementation.

Hence, the success of these applications depends heavily on the detection rate of the image Facial emotion recognition system. Facial emotion recognition from an image can be done by two methods named image-based and feature-based. Image-Based methods treat the whole image as a group of patterns and so each region is classified as the face or non-face. In this method, a window is scanned against the parts of the image. On every scan, the output is computed and the threshold value is compared with the output value of the window on the current part of the image. If it is above the threshold value, then that current part of the image is considered the face. The size of this window is fixed and chosen according to some experiments with the help of training image size. The advantage of image-based methods is the higher percentage of Facial emotion recognition hit rate; however, it is slow in terms of computation as compared to feature-based methods.

Eigenfaces and neural networks are the two examples of the image-based approach. In feature-based methods features such as skin colour, eyes, nose and mouth are separated first from the rest of the image regions. With the extraction of these features, the non-interested regions of the image are not required to process further and therefore the processing time is significantly reduced. In feature-based methods, the skin colour pixels are separated first because the colour processing is faster which results in the separation of other features. The advantage of the feature-based methods is the fast results but less accurate than image-based methods. Another advantage is the ease of implementation in real-time applications. In the project, the feature-based method is implemented. The initial step is to get the image as input and then the feature-based algorithm is applied to detect the face or faces. Once the face region is determined the next is to mark the boundary around it.

In performing a machine learning or deep learning project, selecting the hardware components is a key factor as the project is highly dependent on this component. For the TPU hardware specification, we employed Google Colaboratory (Google Colab). Google Colab is a free cloud service with collab notebooks which has been built on top of Jupyter notebooks and Ubuntu 18.04. Colab notebooks leverage the power of Google's hardware, executing codes in the cloud. It allows for 'end-to-end 'processes involved in facial expression recognition, from pre- processing to evaluating models.

Pre-processing stage: It outlines the steps taken in transforming our datasets due to the different features such as colour, size, number of emotions and resolution to get a unified input for the next stages. Database pre-processing: A database is generated and utilised to test the performance of the proposed models. The database should contain images expressing the 5 different emotions; happiness, sadness, fear, neutral, and surprise. Image pre-processing: The following procedures may be implemented: grayscaling and resizing, face detection and cropping and image enhancement (Dagher, Dahdah, & Al Shakik, 2019).

Face detection and cropping: After the grayscaling and resizing of the images, the detection of faces from the images is performed. The viola jones algorithm implemented in the OpenCV library makes face detection easier for this task. The viola jones algorithm is employed because it detects faces smoothly and at a faster rate. The face detection algorithm detects the face in the images. It operates by looping through the images one after the other, finding shapes that resemble a face and scanning a sub-window around them (Viola & Jones, 2004). The viola jones algorithm aligned and created a bounding box around the detected face in the image. Then, the rectangular area of the box with the detected faces is cropped and saved for further pre- processing steps (Rani & Garg, 2014).

LBP feature extraction: The LBP method is utilised for our feature extraction. As LBP makes use of neighbourhood radius and points, a series of experiments were performed to determine the optimal values for radius and points, respectively. Therefore, for our experiment, 24 and 8 were selected as the number of neighbourhood points and radius respectively which forms a circularly symmetric neighbour set. Then, the LBP operator is performed on all the images. Its computed histogram is a texture-based image descriptor with a total feature vector of dimension 26 (Hossain, 2018). Then the classification stage centres on training the various models by varying and setting hyper parameters, applying data augmentation techniques to improve the models, using different datasets, and studying how the models perform by experimenting with them.

3. CONCLUSION AND RECOMMENDATION

This project worked on recognizing and predicting emotions using machine learning. Facial expressions convey emotional cues and accurate recognition of these cues is a necessary step in the evaluation of interpersonal interactions and for the subsequent application of appropriate social skills. This system possesses a generality advantage and other techniques for optimization that exist and should be discussed for further exploration. This system can be improved with better performance and accuracy with enhanced user-friendliness. For future research, more rules should be implemented to give the system a broader scope and improve the emotion recognition capability.

REFERENCES

1. Jakkula, V. (2011). Tutorial on Support Vector Machine (SVM). School of EECS, Washington State University, 1–13. Retrieved from http://www.ccs.neu.edu/course/cs5100f11/resources/jakkula.pdf
2. Hwang, H. & Matsumoto, D. (2021). Functions of emotions. In R. Biswas-Diener & E. Diener (Eds), Noba textbook series: Psychology. Champaign, IL: DEF publishers. Retrieved from http://noba.to/w64szjxu
3. https://soccerinteraction.com/emotional-intelligence-in-football-players
4. Darwin, C. (1872). The expression of the emotions in man and animals. The Expression of the Emotions in Man and Animals. https://doi.org/10.1037/10001-000.
5. Dubey, S., & Dixit, M. (2019). Facial expression recognition using deep convolutional neural networks. Computing Publications, 8(1), 130–135. https://doi.org/10.1109/KSE.2017.8119447.
6. Duchenne de Boulogne, G. (1862). The Mechanism of Human Facial Expression. Cambridge University Press. https://doi.org/10.1097/00006534-199203000-00032.
7. Ekman, P., & Friesen, W. (1976). Mesauring facial movement.pdf.
8. Ekman, Paul; Davidson, Richard J. (1994). The Nature of emotion: fundamental questions. New York: Oxford University Press. pp. 291–93. ISBN 978-0195089448. Emotional processing, but not emotions, can occur unconsciously.
9. Ekundayo, O., & Viriri, S. (2019). Facial expression recognition: A review of methods, performances and limitations. 2019 Conference on Information Communications Technology and Society, ICTAS 2019. https://doi.org/10.1109/ICTAS.2019.8703619.
10. Gao, K., Mei, G., Piccialli, F., Cuomo, S., Tu, J., & Huo, Z. (2020). Julia language in machine learning: Algorithms, applications, and open issues. Computer Science Review, 37, 100254. https://doi.org/10.1016/j.cosrev.2020.100254.
11. Huang Yunxin, Chen, F., Lv, S., & Wang, X. (2019). Facial expression recognition: A survey. Symmetry, 11(10), 1–28. https://doi.org/10.3390/sym11101189.

12. Hossain, M. M. (2018). Facial Expression Recognition Based on LBP and CNN : A Comparative Study Using SVM Classifier. Rajshahi University of Engineering and Technology.
13. Izard, C. E. (2007). Basic emotions, natural kinds, emotion schemas. Association for Psychological Science, 2(3), 260–280.
14. Koehrsen Will. (2018). Beyond Accuracy: Precision and Recall - Towards Data Science. Media.Com, 19, 1–4. Retrieved from https://towardsdatascience.com/beyond-accuracyprecision-and-recall-3da06bea9f6c
15. Kotu, V., & Deshpande, B. (2015). Data Mining Process. Predictive Analytics and Data Mining, (1), 17–36. https://doi.org/10.1016/b978-0-12-801460-8.00002-.
16. Martinez, B., & Valster, M. (2016). Advances in face detection and facial image analysis. Advances, Challenges, and Opportunities in Automatic Facial Expression Recognition. https://doi.org/10.1007/978-3-319-25958-1.
17. Michel, P., & El Kaliouby, R. (2015). Facial expression recognition using Support Vector Machines. 2015 23rd Signal Processing and Communications Applications Conference, SIU 2015 - Proceedings, 276–279. https://doi.org/10.1109/SIU.2015.7129813.
18. Ojala, T., Pietikäinen, M., & Mäenpää, T. (2002). Multiresolution gray scale and rotation invariant texture classification with local binary patterns. Pattern Recognition, 1842, 404–420. https://doi.org/10.1007/3-540-45054-8_27.
19. Oliphant, T. E. (2007). Python for scientific computing. Computing in Science and Engineering, 9(3), 10–20. https://doi.org/10.1109/MCSE.2007.58.
20. Plutchik, R. (1987). The nature of emotions. Philosophical Studies, 52(3), 393-409. https://doi.org/10.1007/BF00354055.
21. Rani, J., & Garg, K. (2014). An Interface for Extracting and Cropping of Face from Video Frames. International Journal of Computer Science and Information Technologies, 5(3), 4394–4397.
22. Sagi, O., & Rokach, L. (2018). Ensemble learning: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), 1–18. https://doi.org/10.1002/widm.1249.
23. Valero, H. G. (2016). Automatic Facial Expression Recognition. University of Manchester. Retrieved from http://studentnet.cs.manchester.ac.uk/resources/library/thesis_abstracts/MSc16/FullT ext/GamboaValero-Hugo-diss.pdf.
24. Viola, P., & Jones, M. (2004). Robust Real-Time Face Detection Intro to Face Detection. International Journal of Computer Vision, 57(2), 137–154.
25. Watkins, D. (2018). Getting started with Anaconda Python for data science | Opensource.com. Retrieved June 12, 2020, from https://opensource.com/article/18/4/getting-startedanaconda-python.