CO3519 Assignment – Facial Emotion Recognition and Classification using Machine Learning

Author : James Birkenhead | G20983016

## ***Introduction***

Theory of Mind Artificial Intelligence (AI) encompasses the enablement of AI systems to understand human emotions. A Theory of Mind AI would have the capability to interpret human needs, emotions and behaviours and respond appropriately.

Whether current AI technologies such as Large Language Models (LLMs) have achieved Theory of Mind is contested, however a potentially powerful application of current AI capability is for Facial Expression Recognition (FER). The detection of emotions is typically based on the analysis of facial landmark positions such as nose, eyebrows, mouth etc. and changes to those positions can be analysed. These can then be classified to various emotions (European Data Protection Supervisor, 2021).

FER is deemed to be important since much communication is non-verbal, with some studies suggesting up to 60-80%. FER has numerous applications from areas such as education, neuroscience and psychology, to autopilot and more (Huang et al., 2023).

This paper will explore the implementation of a Machine Leaning (ML) algorithm to recognise and classify basic facial emotions, demonstrating the power of AI in this area.

## ***State Of The Literature***

FACIAL RECONGITION – A COMPARISON OF LBP AND HOG

Local Binary Patterns (LBP) are a method of feature extraction which can be applied to facial expression recognition. Faces are processed to extract texture patterns by thresholding a 3x3 neighbourhood of each pixel with the centre pixel value and considering the result as a binary number. A histogram is then formed from these labels that can represent the unique textures of a face. The histogram can then be used to train a machine learning model recognize various faces within the images. (Ghorbani, Targhi and Dehshibi, 2015)

Histogram of Oriented Gradients (HOG) is another method of feature extraction that works with histograms, however the process for feature extraction is slightly different. Occurrences are counted of edge orientations in a localized image neighbourhood. These neighbourhoods represent facial contours and textures that can be used to distinguish emotions.

Adouani, Ben Henia, and Lachiri (2019) compared the LBP and HOG methods alongside the Haar like features algorithm. A sequence of videos was taken from the multimodal DEAP database which contains several hundred videos of facial recordings which can be used for emotional analysis. A video sequence was then inputted, converted to grayscale, and the various facial detection techniques were tested, evaluated and compared. The comparison was performed via a True Positive Rate which measured the proportion of faces correctly identified, and a False Negative Rate which measured the proportion of faces which yielded negative outcomes. In total, videos of 7 human participants were used.

Julina and Sree Sharmila (2019) took a similar approach in testing the various algorithms by testing the feature based facial emotion recognition via a sequence of videos. Various frames from the video input were separated, and the faces were detected and extracted using the HOG and LBP techniques. This study also tested classification, although this is out of the scope of this stage of the review. To measure the accuracy of the 2 models, the sum of true positives/negatives was divided by the sum of true positives/negatives and false positives/negatives.

A consensus that can be drawn from the literature is that HOG produces a higher level of accuracy compared to LBP. Adouani, Ben Henia, and Lachiri (2019) found that HOG was more accurate than LBP with a higher true positive rate and lower false negative rate across all 7 of the videos watched. Overall, HOG achieved a 92.68% detection rate and LBP was much inferior with a 32% reduction in correct detection compared to HOG. Likewise, Julina and Sree Sharmila (2019) also concluded that HOG achieved a higher level of accuracy, with HOG achieving an accuracy rating of 87% and LBP achieving an accuracy rating of 64%. While Adouani, Ben Henia, and Lachiri (2019) produced a higher magnitude of accuracy difference between HOG and LBP compared to Julina and Sree Sharmila (2019), this could be explained by differences in the test data across the 2 studies. However, the overall picture remains consistent and suggests that HOG should be chosen as the method to use for facial detection owing to its’ high accuracy compared to LBP.

EMOTION CLASSIFICATION – A COMPARISON OF SVM AND RF

Support Vector Machine (SVM) is a powerful machine learning algorithm which can be used for linear and nonlinear classification. SVM identifies an optimal hyperplane – a generalization in an N dimensional space - which is then used to separate various data points into several classes. With the placement of the hyperplane, SVM attempts to maximise the scale of the margin between the closest points of the various classes, known as the support vectors. This helps to improve the level of confidence in the resultant classifications.

Decision Trees are non-parametric supervised learning algorithms which can also be used for classification. Decision Trees consist of a hierarchical tree structure, with a root node that contains a set of branches feeding into internal decision nodes. Branches stemming from these nodes may lead to further internal decision nodes, however the algorithm will end at a leaf node which represents the outcome of the decision made. Since using a single decision tree could be prone to error and inaccuracy, the Random Forest (RF) technique can be used. This involves combining the predictions of multiple decision trees, improving the level accuracy and robustness within the model.

Kremic and Subasi (2016) tested SVM and RF to inform decisions to be made for a mobile computer system which would detect and classify human faces. For their study, they acquired images from the International Burch University (IBU) face image dataset containing over 13000 images of 1680 people and carried out the following…

1. Read the image
2. Detect the skin colour and convert to grayscale
3. Create a histogram to extract features from the faces
4. Classify the faces using SVM and RF
5. Authentication was carried out via verification and identification of the faces.

The accuracy of the algorithms was then compared. For SVM, this study also compared accuracy when changing several parameters.

* Changing the kernel function – this function is a method used to take data as an input and transform it into the required processing data. 2 different kernels were compared – a PUK kernel and a linear kernel. **ADD EXPLANATIONS**
* Changing the classifier (C) value which controls the trade-off between the margin and misclassifications. Generally, a smaller value of C promotes a wider margin with a higher risk of misclassification, and a larger value of C promotes a smaller margin with a lower risk of misclassification.

Nugrahaeni and Mutijarsa (2016) also compared SVM and RF, and also alongside the K Nearest Neighbour (KNN) algorithm. The study used images from the Extended Cohn Kanade (CK+) database which contains 593 video sequences from 123 different subjects of various age, genders and heritage. The training datasets were pre-processed, and faces were detected by locating the centre of the face and getting the x and y positions of main facial features. The distance of the x and y positions from the centre of the face were then stored in an ARFF file. This was then fed into a library and used to train the machine learning algorithms, resulting in numerous evaluation metrics such as accuracy, precision, F-measure and confusion matrix.

In terms of accuracy, the picture is quite mixed across the literature with some conflict. Kremic and Subasi (2016) found that the level of accuracy between the two algorithms was very similar, with RF achieving an accuracy rating of 97.17% and SVM achieving a maximum accuracy of 97.94%. A caveat in this study is that the SVM figure only produced 97.17% under one condition where the value of the classifier was 100 and using a linear kernel. However, the range of accuracy ratings was still small with the lowest accuracy rating being 95.89% which would only be inferior to RF by 2.05%. This concludes that RF is the slightly favourable algorithm over SVM in terms of accuracy, although the difference is very small. However, Nugrahaeni and Mutijarsa (2016) found that for a small amount of training data, SVM outperformed RF with accuracy figures of 80% and 76.97% respectively, although if the amount of training data increased, then this reversed with RF producing a 98.85% accuracy rating and SVM producing 90%. A potential explanation for the discrepancy could be related to the datasets used. A limitation of both studies is that they did not specify which images they used, or in the case of Kremic and Subasi (2016), how many or which images they used from the IBU dataset. This means there could’ve been potential bias in the images used for training and testing such as sex and ethnicity. However, since this limitation is shared across the papers, a conclusion that can be drawn from this is that RF has the highest potential accuracy out of the two algorithms, however this will require a larger amount of training data to be significantly stronger than SVM. If the amount of training data available is small, then SVM may be preferable with the appropriate configuration used by Kremic and Subasi (2016), since it was able to produce similar results to RF.

Support Vector Machines (SVM)

Decision Trees/Random Forest

**Much literature uses deep learning, however traditional machine learning is still sufficient for this scope.**

**Be clear on the specific use case for this**

**ENSURE FACIAL RECOGNITION 2D ONLY**

## ***Datasets***

## ***Model Evaluation***

## ***Demonstration***

## ***Conclusion***

## ***References***

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