Altered emotion recognition from psychiatric patient profiles using Machine Learning

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Abstract. Mental illnesses influence the emotion recognition capabilities of those who suffer them. This article presents a study that involves the prediction, using multi-class classification models, of several human standard emotions from facial expressions. It is based on a publicly available dataset for emotion recognition that includes socio-demographic information and psychiatric profiles of individuals with mental illnesses. The study aims to explore how effectively these models can identify and classify emotions based on facial cues, considering the diverse psychiatric backgrounds of the subjects. It also aims to investigate to what extent the severity of the psychiatric condition affects the level of certainty of the predictions.

1 Introduction

Effectively processing social information allows us to build and sustain social and interpersonal relationships [1], where the accurate interpretation of facial expressions, in particular, is crucial for achieving effective social interactions [2]. However, it is known that social perceptions, and especially the perception of emotions, can be disrupted by different mental illnesses, such as depression [3], anxiety [4], insomnia [5], or mania [6], among others. In this brief study, we propose to build several machine learning (ML) multi-class classification models from a publicly available dataset concerning emotion recognition from faces from individuals with different psychiatric profiles. The resulting ML models describe the patterns of emotion recognition according to the sociodemographic and psychiatric profiles of the individuals. To enrich the interpretability of these models, the probabilities they assign to the prediction of the different classes are taken into account. The ultimate goal of the study is the investigation of emotion recognition capabilities from visual processing of human faces.

2 Materials

The data under study, which are publicly available [7], comprise information about six types of emotions for 572 individuals with diverse mental illnesses, in-

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cluding insomnia, anxiety, depression, mania, psychotic experiences and schizotypal traits. The identification of emotions is carried out by visual observation of a set of 56 different faces selected from the Karolinska Directed Emotional Faces database [8]. The images comprise six cross-culturally accepted types of emotions, namely fear, anger, disgust, happiness, sadness, surprise, and neutrality. Each participant in the study is asked to evaluate the six different types of emotions from face images corresponding to eight different persons. Therefore, the dataset presents evidence concerning the prevalence of perceptual distortions in emotional face recognition among individuals exhibiting the aforementioned mental illnesses.

The original dataset was preprocessed to select the information related to the emotion recognition for each image during the trial, as well as the sociodemographic information of the individuals and features related to their psychological profile. It includes age, gender, the assessment of anxiety with the 7-item Generalized Anxiety Disorder Scale (GAD-7), the evaluation of depression using the 9-item patient health questionnaire (PHQ-9), the severity of symptoms of mania assessed with the Mood Disorder Questionnaire (MDQ), severity of insomnia symptoms according to the Insomnia Severity Index (ISI), psychotic-like experiences by the Prodromal Questionnaire 16 (PQ-16) and schizotypal personality traits according to the Short-Form Oxford-Liverpool Inventory of Feelings and Experiences scale. The final dataset consists of $31,976$ (572 individuals $\times$ 7 emotions $\times$ 8 images-per-emotion) rows and 14 columns.

3 Methods

Several supervised classifiers were trained for the prediction of the emotion recognition by the individuals, including Decision Trees (DT), Random Forest (RF) and Multi-Layer Perceptron (MLP) Artificial Neural Networks. First, a hyper-parameter search was carried out allocating 80% of the data for training and 20% for best parameter configuration search. Parameter optimization was accomplished using a randomized search method described in [9]. The parameter search yielded an optimal model for RF using 1,600 estimators, maximum depth of 10 and bootstrapping for sampling. For DT, the optimal configuration was found for a maximum depth of 10, splitting criterion Gini and a number of minimum sample per leaf of 4. For the MLP, the best model was found to have three hidden layers with 100 neurons in each, using an adaptive learning rate initialized at 0.001, Relu activation function and a Stochastic Gradient Descendant solver for optimization. After hyper-parameter tuning, the performance of the models was evaluated using 3-fold cross-validation (CV), measuring accuracy (ACC), precision (PRE), recall (REC), and the F1 score (F1).

4 Results

Table 1 (left) shows the overall performance of the optimized DT, RF and MLP models using stratified 3-fold CV. All three models perform similarly, achieving values of accuracy, precision, recall and F1-score around 0.75, with MLP and RF performing slightly better than DT. Table 1 (right) itemizes the performance of the MLP at the per-class level (DT and RF not shown here for the sake of brevity), revealing important differences between emotions in the recognition capabilities. The model performs best for the recognition of Happiness achieving an F1-score of 0.94. Other correctly recognized emotions are Afraidness, Disgust (D) and Surprise (Su), achieving F1-scores in a range 0.83-0.88. Nevertheless, the model performs poorly in the recognition of Sadness (Sa) and Fear (F), barely achieving F1-scores of 0.53 and 0.32, respectively.

M	**ACC**	**PRE**	**REC**	**F1**
MLP	0.78	0.75	0.74	0.74
RF	0.78	0.75	0.75	0.75
DT	0.76	0.72	0.72	0.72

C	**ACC**	**PRE**	**REC**	**F1**
A	0.90	0.81	0.90	0.85
D	0.88	0.79	0.88	0.83
F	0.39	0.38	0.39	0.32
H	0.96	0.93	0.96	0.94
N	0.82	0.72	0.82	0.74
Sa	0.66	0.44	0.66	0.53
Su	0.92	0.85	0.92	0.88

Table 1: Left: Metrics of the performance of the three models (M). Right: Per class (C) performance for the MLP model.

In order to gain further insights about the level of uncertainty of the emotion recognition process, the probabilities assigned by the model to the six emotion classes in an individual prediction are analyzed. The probability of the six neurons of the output layer of the MLP are averaged for the set of predictions for each type of emotion from all individuals participating in the study. Table 2 shows the mean probabilities the MLP assigns to each of the six emotions. As expected from the per-class performance results, the model shows a low level of uncertainty for the emotions which are recognized with a high accuracy (Afraidness, Happiness and Surprise), with probabilities ranging from 0.82 to 0.96. On the contrary, Fear and Sadness yield high uncertainties. In particular, the model shows a high level of uncertainty for Fear, as there is no clear difference for the true class with regard to the probabilities of prediction of other classes. The model assigns nearly identical probabilities for the true class (Fear) and for Surprise (0.31 and 0.32, respectively), while also yielding relatively high probabilities of 0.19 to Disgust and 0.13 to Sadness. For Sadness (Sa), the average probabilities also show uncertainty. In this case, the true class is predicted with only 0.67 of probability on average, what may come to explain, to some extent, the lower per-class accuracy for Sadness.

The results reported in Table 2 are the mean probabilities derived from the emotion recognitions of the 572 individuals for 56 images each. They provide an overview of the level of uncertainty associated to emotions recognition. Fear and Sadness are the emotions with highest levels of uncertainty. However, the study comprises individuals suffering very different mental illnesses, which motivates a more detailed investigation about the impact of specific psychological disor-

True Emotion	Predicted Class A	D	F	H	N	Sa	Su
A	0.90	0.05	0.01	0.00	0.01	0.02	0.01
D	0.06	0.88	0.01	0.00	0.00	0.04	0.01
F	0.04	0.19	0.31	0.00	0.01	0.13	0.32
H	0.00	0.01	0.00	0.96	0.01	0.01	0.00
N	0.05	0.02	0.01	0.01	0.82	0.09	0.0
Sa	0.02	0.07	0.09	0.00	0.08	0.67	0.06
Su	0.00	0.01	0.04	0.01	0.01	0.01	0.92

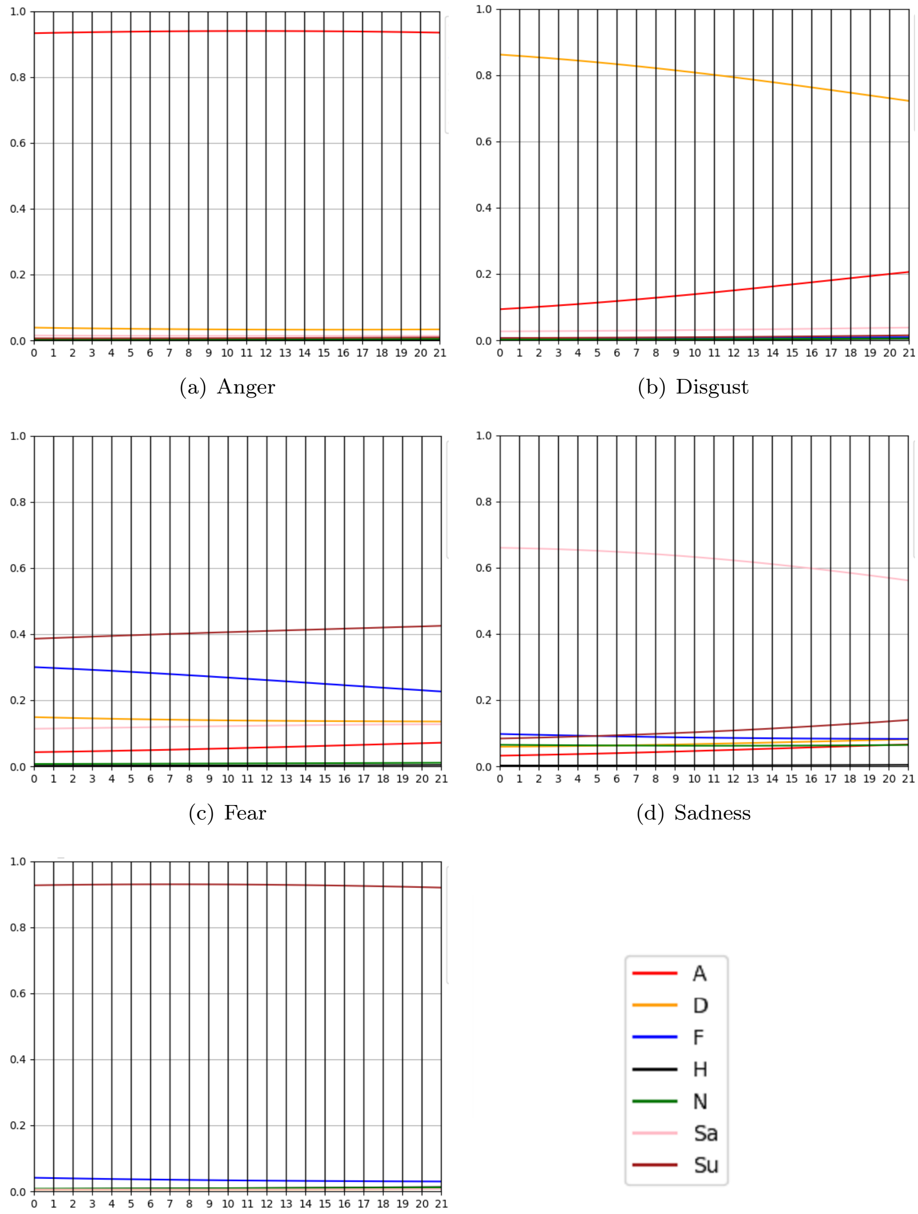
Table 2: The probability of prediction of each emotion with respect the outcome classes of the MLP model. Average values are shown.

der's severity on the emotion recognition capabilities. As an illustration of this, the probabilities for emotion predictions were analyzed according to severity of anxiety, which is evaluated by means of the GAD-7 scale, where the thresholds of 5, 10, and 15 of a total scale of 21 points indicate mild, moderate, and severe anxiety levels respectively. The impact of anxiety on the emotion recognition capability is analyzed using a baseline patient profile of 21.7 years of age (the average age in the study), and a healthy profile with regard to depression, insomnia, mania, psychotic like experiences and schizotypal personality traits expressed as scores close to 0 for the respective attributes.

Figure 1 displays the prediction probabilities of the MLP for the different emotions as a function of the level of anxiety. Only a selection of emotions are reported for the sake of brevity. While for Anger, Happiness (not displayed) and Suprise the prediction probability of the true class is high and stable, there are some other emotions for which the recognition capability is impacted by the level of anxiety. For Fear, the probabilities in Image 1(c) vary with the level of anxiety. From a baseline situation (anxiety score=0), the MLP already assigns 0.39 to the prediction of Surprise and 0.3 to the prediction of Fear and some lower probabilities to other emotions. As the level of anxiety increases, the probability for predicting Surprise rises, while the probability for predicting the true class, i.e. Fear, decreases. This case shows clearly that the uncertainty of the recognition of Fear increases with higher levels of anxiety and also that Fear is often perceived as Surprise. Another interesting examples where the impact of anxiety is noticeable are Disgust, Neutral (not displayed) and Sadness . In these cases, the uncertainty of recognition rises with anxiety as the probability of the the true class prediction decreases with higher levels of anxiety. Disgust is likely to be perceived as Anger, Neutrality is likely to be confused with Sadness or Anger, and Sadness is likely to be misperceived as Surprise or Fear.

5 Discussion and Conclusion

Several ML models were able to learn, with reasonable and similar effectiveness, the patterns of emotion recognition elicited by mental illness patients in a



(a) Anger (b) Disgust

(c) Fear (d) Sadness

(e) Surprise (f) Legend

Fig. 1: Probabilities for emotion prediction of the MLP (y-axis) according to the degree of anxiety (x-axis).

multi-class prediction scenario. Nevertheless the models showed emotion-specific differences. Fear and Sadness resulted the most difficult to correctly predict and the analysis of the prediction probabilities of the multiclass classifier clearly associated bad classification with high prediction uncertainty. In particular, Fear is likely to be misperceived as Surprise, while Sadness is likely to be misconstrued as Surprise. Furthermore, the study measured the impact of anxiety on the levels of prediction certainty. In general, higher levels of anxiety reduced the probability of prediction of the true class for emotions already uncertain in terms of prediction, demonstrating that the correct recognition of emotions is influenced negatively by higher levels of anxiety. In future research, this information will be systematically expanded to explore the relative impact of other mental illnesses, following the example, in this study, of the impact of anxiety.

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