Introduction V1

Emotions are an important part of the human species. Ever since we were born, we have been guided by our feelings. Even if we only feel them internally, we usually also show them externally. This helps our fellow human beings to understand what emotional state we are in without having to engage in a verbal exchange. However, it is not always easy to read the emotions of strangers from their facial expressions. So our question is, can we train a neural network to recognize human emotions from facial expressions? Such a machine learning model would enable us to automatically record and process data on emotions. This would allow us to analyse and improve advertising, films, series or any content that aims to trigger certain emotions in viewers using statistical data.

Introduction V2

## Emotions: The Unspoken Language of Humanity

From our very first cries as newborns, emotions have served as a powerful internal compass, guiding our thoughts and actions. But emotions are not just limited to the inner realm. We naturally express them outwardly through facial expressions, offering a window into our emotional state for those around us. This nonverbal communication is fundamental to human interaction, allowing us to connect and understand each other without speaking a single word.

However, deciphering the emotions of strangers, particularly through facial expressions, can be a complex task. This is where the exciting potential of artificial intelligence emerges. Can we harness the power of neural networks to train a system that can recognize human emotions from facial expressions?

Imagine a machine learning model capable of automatically interpreting and recording emotional data. This would unlock a treasure trove of insights, allowing us to analyze and optimize content across various mediums – advertising, film, television – with the power of data-driven emotional response. By understanding how viewers react emotionally, we could create more impactful and targeted content, ensuring our message resonates on a deeper level.

This exploration into emotional recognition through AI is not just about technological advancement; it's about unlocking a new layer of understanding in human communication. It's about empowering machines to bridge the gap between the internal world of emotions and the external world of expression.

Literature review:

Smote:

Literature review: SMOTE for imbalanced classification with application to emotion recognition

**Introduction**

Class imbalance is a major challenge in machine learning classification tasks where one or more classes have far fewer data points compared to the majority class. This can lead to biased models that favor the majority class and perform poorly on the minority class. The Synthetic Minority Oversampling Technique (SMOTE) is a widely used technique that corrects the imbalance between classes by oversampling the minority class, creating a more balanced data set for training.

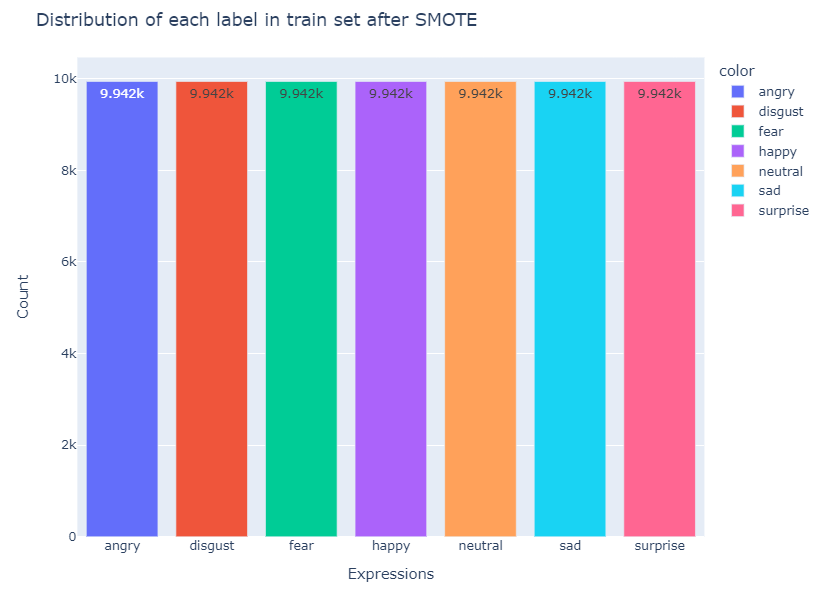
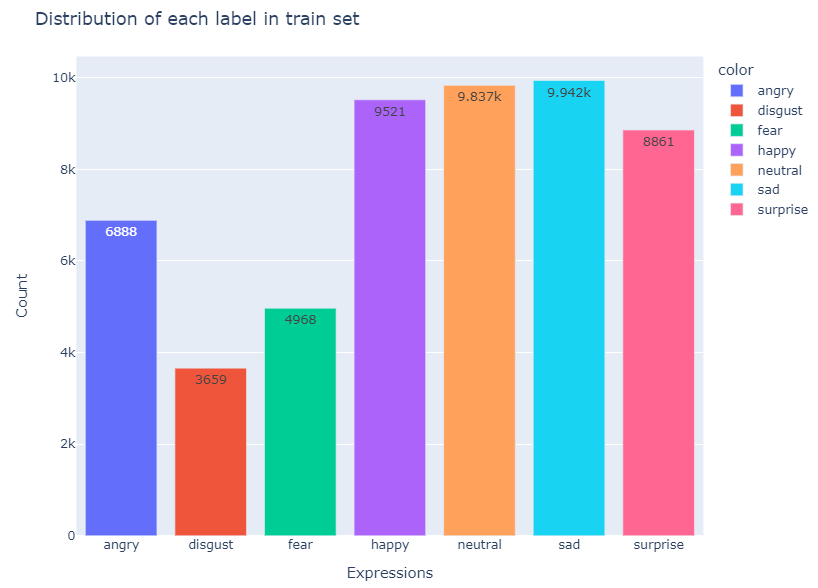
**SMOTE methodology**

The source code "SMOTE for Imbalanced Classification with Python" by Machine Learning Mastery provides a detailed explanation of the SMOTE algorithm. SMOTE generates synthetic data points for the minority class. These new data points are generated by interpolating between existing samples of the minority class. This involves selecting a minority class sample, identifying its nearest neighbors, and then generating new data points along the line segments connecting the sample to its neighbors.

**Application in the recognition of emotions**

In our case, we combined the expw and fer2013 datasets to improve the training data for an AI model for emotion recognition. However, despite combining the datasets, the problem of class imbalance remained. SMOTE was used to compensate for the minority emotion classes and effectively equalize the overall dataset for training.

Figure 1: Distribution before and after SMOTE



**Advantages of SMOTE for emotion recognition**

Using SMOTE to eliminate class imbalance in emotion recognition offers several advantages:

Improved minority class recognition: By balancing the emotion classes, SMOTE ensures that the model recognizes both majority emotions and also adequately represents those of the minority, which leads to better recognition of minority emotions.

Reduced bias: SMOTE mitigates bias towards the majority class and prevents the model from favoring one emotion over others.

Improved overall performance: By effectively recognizing all emotions, the overall performance of the model in recognizing emotions is likely to be improved.

**Implementation considerations**

When implementing SMOTE for emotion recognition, the following factors need to be considered:

Selection of hyperparameters: SMOTE has hyperparameters, such as the number of nearest neighbors and the extent of oversampling, that can affect its performance. These hyperparameters should be carefully tuned based on the specific dataset and task.

Evaluation metrics: For emotion recognition, appropriate metrics such as F1-score or precision-recall curves should be used to evaluate the model's performance for both majority and minority emotion classes.

Possible limitations: SMOTE may introduce noise or overfitting into the data. Careful evaluation and validation is required to ensure that SMOTE is useful for the task at hand.

**Conclusion**

SMOTE is a valuable tool for addressing class imbalances in emotion recognition tasks. By balancing the emotion classes, SMOTE helps to improve the model's ability to effectively recognize a wider range of emotions. However, successful implementation requires careful consideration of hyperparameters, evaluation measures and potential limitations.

**Additional application examples**

In addition to the emotion recognition application described in the source text, SMOTE can also be used for various other classification tasks where class imbalance is a problem. For example, SMOTE can be used to equalize data sets in:

Fraud detection: identification of fraudulent transactions from a large number of legitimate transactions.

Medical diagnosis: Classification of patients based on their symptoms and medical history.

Churn prediction: Predicting which customers are unlikely to use a service.

By effectively handling class imbalances, SMOTE can contribute to improved performance and more reliable decision making on a variety of classification problems.

Brownlee, J. (2021, March 17). *SMOTE for Imbalanced Classification with Python*. Machine Learning Mastery. Retrieved June 7, 2024, from https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/