Emotion Prediction Using Support Vector Machine (SVM) Using Image

Submitted By

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1. Project Overview

The goal of this project is to create an SVM-based model to predict emotions from images, specifically from facial expressions. Facial expression recognition is a challenging task, but with effective preprocessing, feature extraction, and SVM optimization, the project aims to achieve accurate multi-class emotion classification. The project will explore the following:

- **Image Processing:** Methods to enhance image data for better model performance.
- **Feature Extraction:** Techniques to extract meaningful features from facial images.
- **Optimization:** Tuning the SVM model to improve classification accuracy.

2. Problem Statement

Understanding emotions through facial expressions is essential in several fields, such as:

- **Psychology:** For analysing emotional responses.
- **Marketing:** To understand customer reactions.
- **Security:** For detecting emotional states in high-stress situations.
- **Human-Computer Interaction:** To make systems more responsive to users' emotions.

However, predicting emotions from facial expressions is challenging due to:

- **Variations in Facial Structures:** Different individuals have unique facial features.
- **Changes in Expressions:** Emotions can be subtle or mixed, making them difficult to detect accurately.

This project aims to bridge the gap by using **Support Vector Machine (SVM)** classifiers to predict emotions from images. The goal is to classify multiple emotions such as happiness, sadness, anger, etc., from facial expressions in an automated manner.

3. Project Objectives

1. **Preprocessing:**
    - **Image Resizing:** Standardise the image size for uniformity in model input.
    - **Grayscale Conversion:** Convert colour images to grayscale to reduce computational complexity while retaining essential features for emotion recognition.
    - **Normalisation:** Scale pixel values between 0 and 1 to improve model performance and convergence speed.
2. **Feature Extraction:**
    - **Histogram of Oriented Gradients (HOG):** A technique that captures edge information crucial for identifying facial features related to emotions.
    - **Other Descriptors:** Consider using Local Binary Patterns (LBP) or Gabor Filters to capture texture and spatial patterns on the face.
3. **Model Training:**
    - **SVM Training:** Train SVM models using different kernels (linear, Radial Basis Function (RBF)) for emotion classification.
    - **Cross-validation:** Implement cross-validation to ensure the model generalises well and is not overfitted to the training data.
    - **Kernel Selection:** Test both linear and non-linear kernels to determine which works best for the facial expression data.
4. **Model Evaluation:**
    - **Metrics:** Evaluate the SVM model using **accuracy**, **precision**, **recall**, **F1-score**, and **confusion matrix** to assess performance.
    - **ROC Curve:** Analyse the model's ability to discriminate between emotions at different classification thresholds.
5. **Optimization:**
    - **Hyperparameter Tuning:** Use grid search or randomised search to find the best values for hyperparameters like C (penalty parameter), kernel type, and gamma (for RBF).
    - **Performance Improvements:** Test various techniques like feature scaling, dimensionality reduction (e.g., PCA), and kernel functions to improve the model's accuracy.

4. Data Source

- **Dataset:** The **FER 2013 (Facial Expression Recognition 2013)** dataset available on **Kaggle** will be used. It contains 35,887 labelled grayscale images of facial expressions categorised into seven emotions:
    1. **Anger**
    2. **Disgust**
    3. **Fear**
    4. **Happiness**
    5. **Sadness**
    6. **Surprise**
    7. **Neutral**

The dataset includes multiple examples for each emotion, making it suitable for training a multi-class classifier.

- **Preprocessing:** Since the images are already in grayscale, further preprocessing will involve:
    - Resizing images to a standard dimension (e.g., 48x48 pixels).
    - Normalizing pixel values.
    - Augmenting the dataset to improve model robustness.

5. Methodology

1. **Data Preprocessing:**
    - **Grayscale Conversion:** If the dataset contains coloured images, convert them to grayscale.
    - **Image Resizing:** Resize images to a consistent size (e.g., 48x48 or 64x64 pixels) to standardise input for the classifier.
    - **Normalisation:** Scale pixel values to a range of 0 to 1 to speed up model training.
2. **Feature Extraction:**
    - **Histogram of Oriented Gradients (HOG):** Extract edge features to represent the shape and structure of the face. This method is useful for recognizing emotion-related facial features like smiles, furrowed brows, etc.

    - **Other Descriptors:** Use Local Binary Patterns (LBP) or Gabor Filters, which capture the texture patterns of the face that can vary with different emotions.
3. **SVM Model Training:**
    - **Kernel Selection:** Experiment with different kernels (e.g., linear, RBF) to determine which produces the best results for emotion classification.
    - **Cross-validation:** Use k-fold cross-validation to ensure that the model performs consistently across different subsets of the data.
4. **Model Evaluation:**
    - **Confusion Matrix:** A confusion matrix will show how well the model is able to classify each emotion.
    - **Evaluation Metrics:** Use accuracy, precision, recall, and F1-score to evaluate the model. These metrics will provide a comprehensive view of the classifier's performance, especially in multi-class settings.
    - **ROC Curve:** The ROC curve will help assess how well the model differentiates between different classes at varying thresholds.

6. Tools and Technologies

- **Programming Language:** Python
- **Libraries:**
    - **OpenCV:** For image preprocessing (e.g., resizing, normalisation).
    - **scikit-learn:** For implementing SVM and evaluation metrics.
    - **matplotlib:** For visualising results, including the ROC curve and confusion matrix.
    - **NumPy:** For numerical operations like array manipulations.

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7. Expected Outcomes

- **Trained Model:** An SVM classifier capable of predicting emotions from facial expressions with high accuracy.

- **Performance Analysis:** Comprehensive analysis of the model's performance across different metrics (accuracy, precision, recall, F1-score, confusion matrix).
- **Optimization Results:** Insights into the best SVM parameters (e.g., kernel choice, regularisation parameters) for emotion classification.

8. Future Scope

1. **Real-Time Emotion Recognition:**
   - Extend the project to work in real-time, processing webcam feed to detect emotions from live facial expressions.
2. **Deep Learning Models:**
   - Explore convolutional neural networks (CNNs) for comparison, as they have been shown to perform well on image-related tasks, including emotion recognition.
3. **Multimodal Emotion Detection:**
   - Integrate voice or text data along with facial images to create a more robust emotion prediction system.
4. **Transfer Learning:**
   - Leverage pre-trained models like VGG or ResNet to enhance the feature extraction process and improve accuracy.

Conclusion

This project aims to leverage SVM for effective emotion prediction using facial expressions, providing a practical solution for applications in psychology, marketing, and security. The focus on preprocessing, feature extraction, and optimization is expected to lead to a model that performs well in multi-class emotion classification tasks. Future work could extend the model to real-time predictions and explore deep learning alternatives for further improvements.

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