Project title: Facial Emotion detection using Deep learning

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GitHub link: https://github.com/zulfiqarskd17/zulfiqarskd17-facial_expression_recognition_project

Abstract:

Facial Expression Recognition (FER) is a challenging task in computer vision, aimed at automatically identifying emotions from facial images. In this project, we explore the FER2013 dataset, which contains 30,000 grayscale images of faces labeled with one of seven emotions: Angry, Disgust, Fear, Happy, Neutral, Sad, or Surprise. The dataset presents several challenges, including low-resolution images and subtle emotions. Our objective is to build a Convolutional Neural Network (CNN) model in Python using Keras to accurately recognize facial expressions and evaluate its performance on the test set.

Introduction:

Facial expressions are a fundamental aspect of human communication and emotions. Automating the process of recognizing facial expressions has significant applications in fields like human-computer interaction, virtual reality, and affective computing. The FER2013 dataset serves as an essential resource for researchers and developers in this domain. This report presents the process of building and evaluating a facial expression recognition model using the FER2013 dataset.

Data Preprocessing:

The FER2013 dataset consists of images and corresponding labels. To prepare the data for model training, we load the dataset and preprocess it. The grayscale images are reshaped to a standard size of 48x48 pixels, and the pixel values are normalized between 0 and 1. The emotion labels are one-hot encoded to facilitate multi-class classification.

Model Architecture:

We design a CNN model to recognize facial expressions from the preprocessed images. The model architecture comprises Conv2D layers with ReLU activation for feature extraction, MaxPooling2D layers for spatial down sampling, and Flatten layers to convert 2D feature maps into 1D vectors. Dense layers with ReLU activation are used for classification, and a Softmax activation is employed in the output layer to predict the probabilities of each emotion class.

Model Training and Evaluation:

The dataset is split into training and testing sets, and the model is compiled with categorical cross-entropy loss and the Adam optimizer. We train the model on the training set for a specific number of epochs and monitor the training and validation accuracy. After training, we evaluate the model on the test set to assess its generalization performance.

Performance Enhancement Strategies:

To improve the model's accuracy, we apply several performance enhancement techniques. Data Augmentation is employed to generate additional training data by applying random transformations to existing images, increasing the dataset's diversity. Learning Rate Scheduling adjusts the learning rate during training to optimize convergence and prevent overshooting. Dropout Regularization is introduced to reduce overfitting by randomly deactivating neurons during training. Hyperparameter Tuning involves experimenting with various architectures and hyperparameters to find the optimal configuration. Additionally, we explore Transfer Learning, leveraging pre-trained models for feature extraction and fine-tuning on our dataset.

Results and Discussion:

The CNN model achieves a significant improvement in facial expression recognition accuracy after implementing the performance enhancement strategies. Data Augmentation increases the training set's size and boosts generalization performance. Learning Rate Scheduling prevents overfitting and helps fine-tune the model efficiently. Dropout Regularization effectively reduces overfitting, allowing the model to generalize better. Hyperparameter Tuning enables us to discover the best configuration for our dataset. Transfer Learning proves valuable in cases with limited data, leveraging pre-trained models to improve recognition accuracy.

Conclusion:

In conclusion, this project demonstrates the successful implementation of a facial expression recognition model using the FER2013 dataset. We achieved improved accuracy by employing various performance enhancement strategies, ensuring the model's capability to recognize emotions accurately. The FER2013 dataset serves as a valuable resource for researchers and developers working on facial expression recognition algorithms, and further research in this domain promises exciting possibilities in real-world applications