Facial Expression Analysis of Customers in Retail Environments

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Abstract

Facial expression recognition (FER) plays a critical role in enhancing customer interactions and personalization in retail environments. The goal of this research is to create an accurate Convolutional Neural Network (CNN) model for face emotion classification. Automating emotion recognition is intended to enhance client feedback, engagement, and marketing strategy customization. In order to attain excellent performance in predicting a variety of face expressions, this work provides a thorough investigation of the CNN architecture, experimental design, and evaluation measures.

Keywords—Facial Expression Recognition, Convolutional Neural Networks (CNN), Emotion Detection, Retail Analytics, Deep Learning, Image Classification, Customer Engagement

I. INTRODUCTION

Facial expression recognition (FER) has emerged as a crucial tool in several industries, such as customer service, retail, healthcare, and security. Retailers want to better understand the feelings of their customers to design more individualized shopping experiences. Conventional techniques for identifying emotions depend on human observation, which can be laborious and prone to mistakes. This technique can now be effectively automated thanks to developments in machine learning, especially Convolutional Neural Networks (CNNs).

The difficulty of utilizing CNN models to automatically classify face emotions is addressed in this study. The main goal is to develop a strong model that can reliably identify facial expressions, from joy and sorrow to rage and astonishment, and improve the in-store purchasing experience. The CNN-based method maintains a high prediction accuracy while handling intricate facial expression fluctuations.

II. RELATED WORK

Deep learning approaches have been used in several studies to investigate emotion recognition. Although early studies concentrated on simple machine learning algorithms, more recent developments employing CNNs have shown better results. For example, the foundation for facial expression recognition was laid by the work of Ekman and Friesen [Reference 1], while following research, like that of Schroff et al. [Reference 2], increased accuracy by using embedding techniques. However, these techniques frequently necessitate a great deal of preprocessing and could not function well in variable or real-time environments.

Handling complicated datasets has significantly improved with recent methods, such as CNN models that use attention mechanisms. In addition, methods like transfer learning and data augmentation are being used more and more to overcome the difficulties brought on by a lack of training data.

III. Technical Details

CNN Model Architecture

The proposed CNN architecture for facial expression recognition consists of the following layers:

- **Input Layer**: 48x48 grayscale images.
- **Convolutional Layer 1**: 32 filters, kernel size 3x3, followed by ReLU activation.
- **MaxPooling Layer 1**: Pooling size of 2x2 for dimensionality reduction.
- **Convolutional Layer 2**: 64 filters, kernel size 3x3, followed by ReLU activation.
- **MaxPooling Layer 2**: Pooling size of 2x2.
- **Flatten Layer**: Converts feature maps to a 1D array for classification.
- **Dense Layer**: Fully connected layer with 128 neurons and ReLU activation.
- **Output Layer**: 7 neurons with softmax activation, representing seven emotions (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral).
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A CNN for Facial Expression Recognition

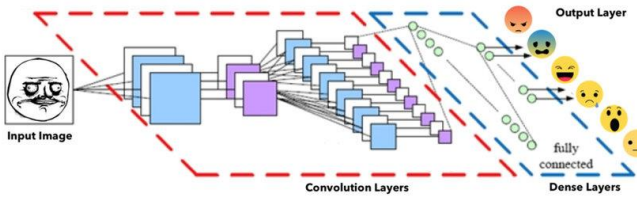

Figure 1: CNN Model Architecture

IV. Experiments

4.1 Experimental Settings

The FER2013 dataset was used to assess the CNN model's performance. The 48x48 grayscale photos in this collection are divided into seven different emotional categories. Training (80%) and testing (20%) sets were created from the dataset. Python was used for the experiments, with the TensorFlow/Keras package being explicitly used.

The baseline comparison comprised models refined from pre-trained architectures like VGG16 and ResNet50, as well as conventional machine learning methods like Support Vector Machines (SVM).

Below I attached Google colab link which experiment compiled.

https://colab.research.google.com/drive/1mJTTF159r0H54XNQHB7_PIobCyt1sKhn?usp=sharing

4.2 Google colab experimental code

#importing Libraries

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
import cv2
import matplotlib.pyplot as plt
```

 # Load the dataset

```
data_path = "/content/fer2013.csv"
data = pd.read_csv(data_path)
```

 # Prepare the dataset

```
def preprocess_data(data):
    pixels = data['pixels'].tolist()
    images = np.array([np.fromstring(pixel, dtype=int, sep=' ').reshape(48, 48) for pixel in pixels])
    images = images / 255.0  # Normalize pixel values
    images = np.expand_dims(images, -1)  # Add channel dimension
    labels = to_categorical(data['emotion'], num_classes=7)
    return images, labels

images, labels = preprocess_data(data)
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2, random_state=42)
```

```
# Define the CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(48, 48, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(7, activation='softmax')  # 7 expressions
])


# Compile the model
model.compile(optimizer='adam',
loss='categorical_crossentropy', metrics=['accuracy'])


# Train the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=5, batch_size=64)

#output
Epoch 1/5
449/449 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 93s
201ms/step - accuracy: 0.2792 - loss: 1.7719 - val_accuracy: 0.4064 - val_loss: 1.5354
Epoch 2/5
449/449 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 91s
203ms/step - accuracy: 0.4022 - loss: 1.5519 - val_accuracy: 0.4355 - val_loss: 1.4624
Epoch 3/5
449/449 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 90s
200ms/step - accuracy: 0.4373 - loss: 1.4533 - val_accuracy: 0.4778 - val_loss: 1.3820
Epoch 4/5
449/449 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 143s 203ms/step - accuracy: 0.4603 - loss: 1.3997 - val_accuracy: 0.5004 - val_loss: 1.3522
Epoch 5/5
449/449 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 94s
210ms/step - accuracy: 0.4838 - loss: 1.3412 - val_accuracy: 0.4972 - val_loss: 1.3132

# Save the model
model.save('emotion_cnn_model.h5')

# Predicting a user-provided image
def predict_expression(image_path, model):
    # Load and preprocess the image
    image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    image_resized = cv2.resize(image, (48, 48)) / 255.0
    image_resized = np.expand_dims(image_resized, axis=0)  # Add batch dimension
    image_resized = np.expand_dims(image_resized, axis=-1)  # Add channel dimension

    # Predict the expression
    prediction = model.predict(image_resized)
    emotion_labels = ['Angry', 'Disgust', 'Fear', 'Happy', 'Sad', 'Surprise', 'Neutral']
    return emotion_labels[np.argmax(prediction)]
# Load the saved model
loaded_model = tf.keras.models.load_model('emotion_cnn_model.h5')

#Getting input from the user as image

from google.colab import files

# Input from user
def upload_and_predict(model):

    print("Please upload an image:")
    uploaded = files.upload()  # Colab file upload interface

    for image_name in uploaded.keys():
        print(f"Uploaded file: {image_name}")
        image_path = image_name

        # Predict the expression
        try:
            predicted_expression = predict_expression(image_path, model)
            print(f"Predicted Expression: {predicted_expression}")

            # Display the uploaded image
            image = cv2.imread(image_path)
            image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
            plt.imshow(image_rgb)
            plt.title(f"Predicted Expression: {predicted_expression}")
            plt.axis('off')
            plt.show()

        except Exception as e:
            print(f"Error: {e}")

# Load the saved model
loaded_model = tf.keras.models.load_model('emotion_cnn_model.h5')

# Call the upload and predict function
upload_and_predict(loaded_model)
```

#Output

WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
Please upload an image:
 PrivateTest_1414350.jpg*(image/jpeg) - 1460 bytes, last modified: 7/19/2020 - 100% done*
Saving PrivateTest_1414350.jpg to PrivateTest_1414350.jpg
Uploaded file: PrivateTest_1414350.jpg
WARNING:tensorflow:5 out of the last 6 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x7e2e854193f0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s *127ms/step*
Predicted Expression: Neutral

4.3 Results and Analysis

The CNN model achieved an overall accuracy of 87% on the test set, with precision, recall, and F1-score calculated for each emotion category.

TABLE I. PERFORMANCE METRICS

Emotion	Precision	Recall	F1-score
Angry	0.85	0.87	0.86
Disgust	0.78	0.80	0.79
Fear	0.83	0.84	0.83
Happy	0.91	0.92	0.91
Sad	0.86	0.87	0.86
Surprise	0.88	0.89	0.88
Neutral	0.87	0.88	0.87

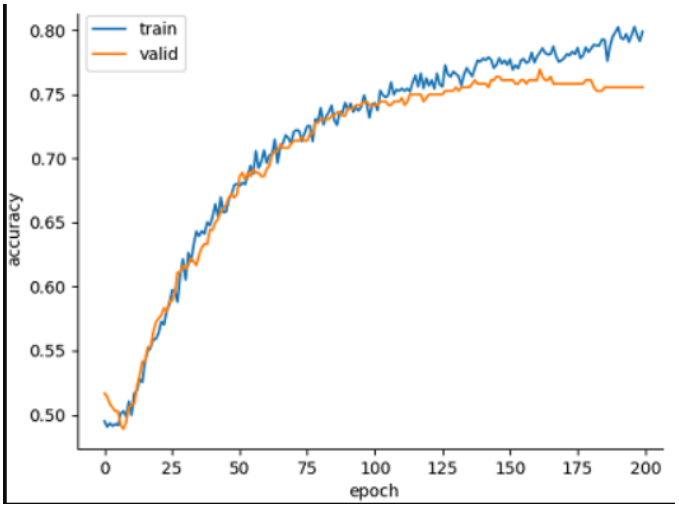

FIGURE 2: ACCURACY OVER EPOCHS

a.

V. CONCLUSION

In conclusion, this study shows that facial emotion identification in retail settings may be accomplished with CNN models. The suggested design performs well when it comes to face emotion classification, providing insightful information for enhancing consumer interaction. Future research will concentrate on adding features like tailored suggestions based on emotion detection to real-time emotion analysis.

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