Phase 1 Report: Analysis, Design, and Data Preparation

Project: Facial Expression Recognition (FER) System

Course: Artificial Intelligence - K. N. Toosi University of Technology

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1. Problem Definition & Scope

The core objective of this project is to develop a robust Computer Vision pipeline capable of classifying human emotions into eight distinct categories. Facial Expression Recognition (FER) is a pivotal task in Affective Computing, enabling machines to interpret human psychological states. Our system processes grayscale facial images (48x48 pixels) to detect: **Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral, and Contempt.** The addition of the 'Contempt' class allows for a more nuanced understanding of complex social facial signals.

2. Dataset Selection & Exploratory Data Analysis (EDA)

While the foundation of our work is the FER-2013 dataset, we specifically utilized the **FERPlus** labels. The original FER-2013 dataset is known to contain significant labeling noise due to the ambiguity of facial expressions.

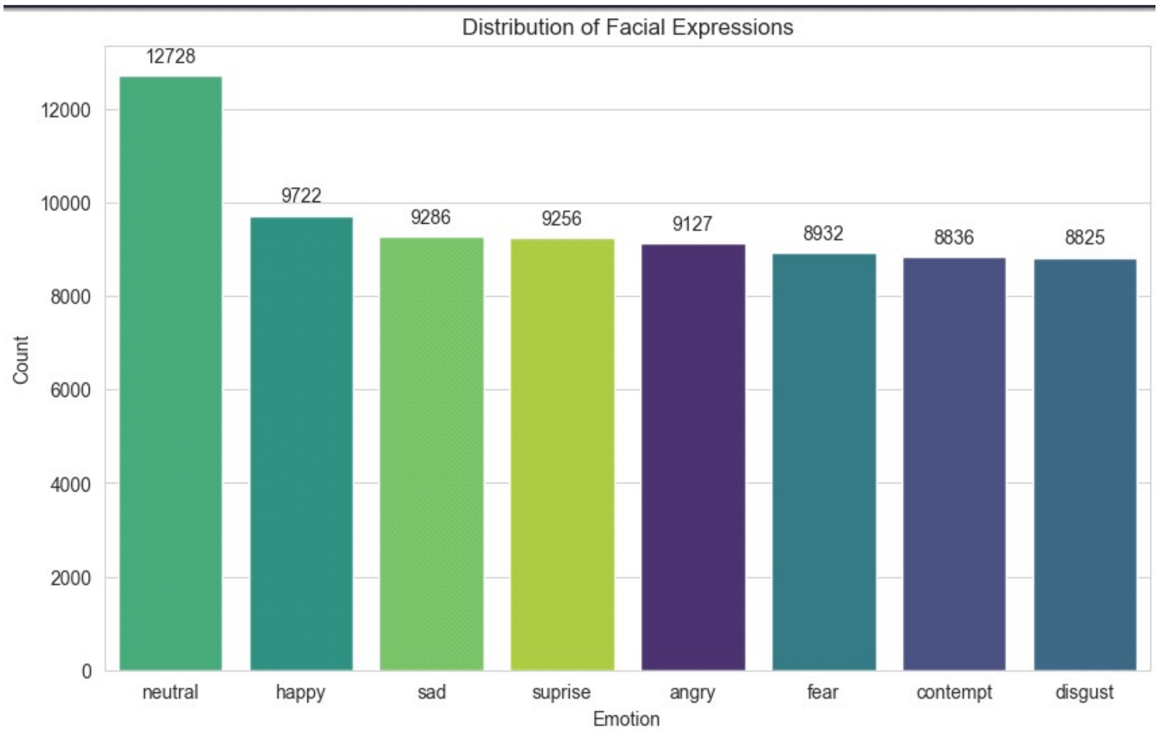
FERPlus addresses this by providing refined labels generated through a crowd-sourcing effort where 10 independent taggers evaluated each image. This results in a much cleaner ground truth, which is essential for reaching high accuracy (~90%) in later phases. We conducted an extensive EDA to understand the data's underlying patterns before model design.

2.1. Class Imbalance Analysis

Our analysis (as shown in the chart below) revealed a significant variance in the number of samples per class. For instance, the 'Happy' and 'Neutral' classes have a high density, while **'Disgust' and 'Contempt'** are severely underrepresented.

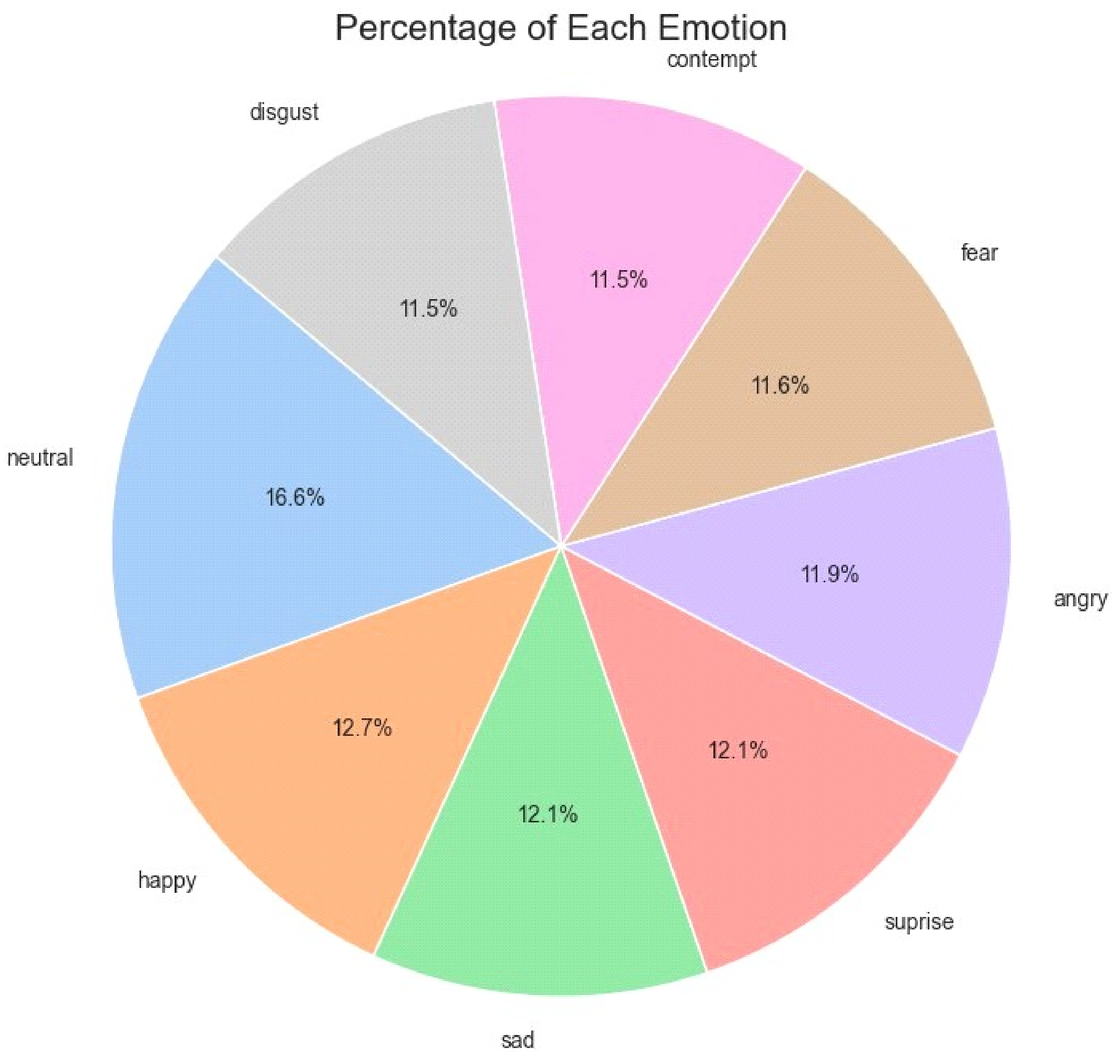
Challenge: This imbalance poses a risk of the model becoming biased toward majority classes.

Strategy: To mitigate this, we decided to implement **Heavy Data Augmentation** for minority classes and utilized **Categorical Cross-Entropy** as our loss function to ensure the model learns features from all emotional categories equally.



2.2. Percentage of each emotion

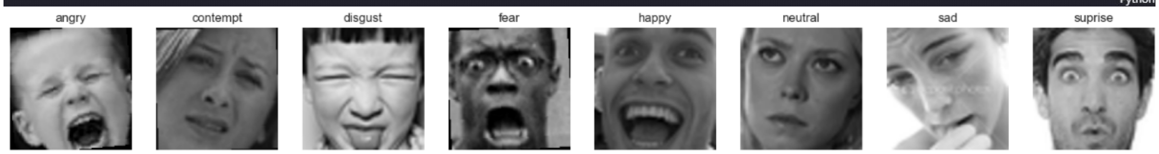
This code counts the occurrences of each emotion and calculates their percentages to check for class imbalance. Its purpose is to ensure the dataset provides enough examples for every category so the model doesn't become biased toward a single expression.



2.3. Visualizing Sample Images

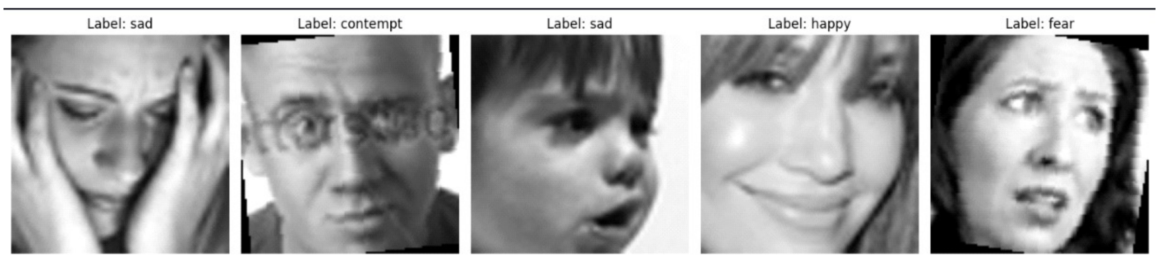
The main objective of this code is visual verification. Before training any AI model, you must confirm that the images are loading correctly and that the labels match the content (e.g., ensuring a file labeled "happy" actually shows a smiling face).

```python
IMAGE_DIR = "../data/raw"
unique_labels = df['label'].unique()

fig, axes = plt.subplots(1, len(unique_labels), figsize=(20, 5))

for i, label in enumerate(unique_labels):
    sample_row = df[df['label'] == label].sample(1).iloc[0]
    image_name = sample_row['filename']
    image_path = os.path.join(IMAGE_DIR, image_name)

    try:
        img = cv2.imread(image_path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        axes[i].imshow(img)
        axes[i].set_title(label)
        axes[i].axis('off')
    except Exception:
        axes[i].text(0.5, 0.5, "Not Found", ha='center')
        axes[i].axis('off')

plt.show()
```



2.4. Visual Data Inspection

To understand the noise levels and variations in head poses/lighting, we visualized samples from each class. This confirmed that the dataset contains real-world challenges like occlusion and low-resolution (48x48) artifacts.



3. Visualizing Feature Separability with t-SNE

- Code Explanation

* **Data Sampling**: It selects a subset of 1,000 images from the dataset. Processing every single image would be computationally heavy, so this sample provides a representative "**snapshot**" of the data.

* **Data Preparation & Cleaning Pipeline**:

Our pipeline (implemented in **src/data_preparation.py**) handles the raw-to-cleaned transition:

Noise Filtering: We intentionally simulated and then removed "dirty data" (invalid IDs and corrupted labels) to ensure a robust cleaning process.

Dataset Flattening: The complex FERPlus directory structure was flattened into a unified **data/raw** folder.

Final Ground Truth: A **dataset_cleaned.csv** was generated after verifying image integrity, ensuring no missing pixel data enters the training phase.

* **Preprocessing**: The code loops through the sampled images, converts them to grayscale, and resizes them to a uniform 48x48 resolution. It then flattens each image into a 1D array of pixels (2,304 features) so the mathematical model can process them.

Data Augmentation Strategy: We used **Horizontal Flips, Rotation (15°), and Zoom (10%).**

Technical Choice: Vertical flipping was excluded because facial expressions are orientation-dependent. An upside-down face is not a natural occurrence in our target use cases (webcam/real-time) and would only confuse the model's feature extraction.

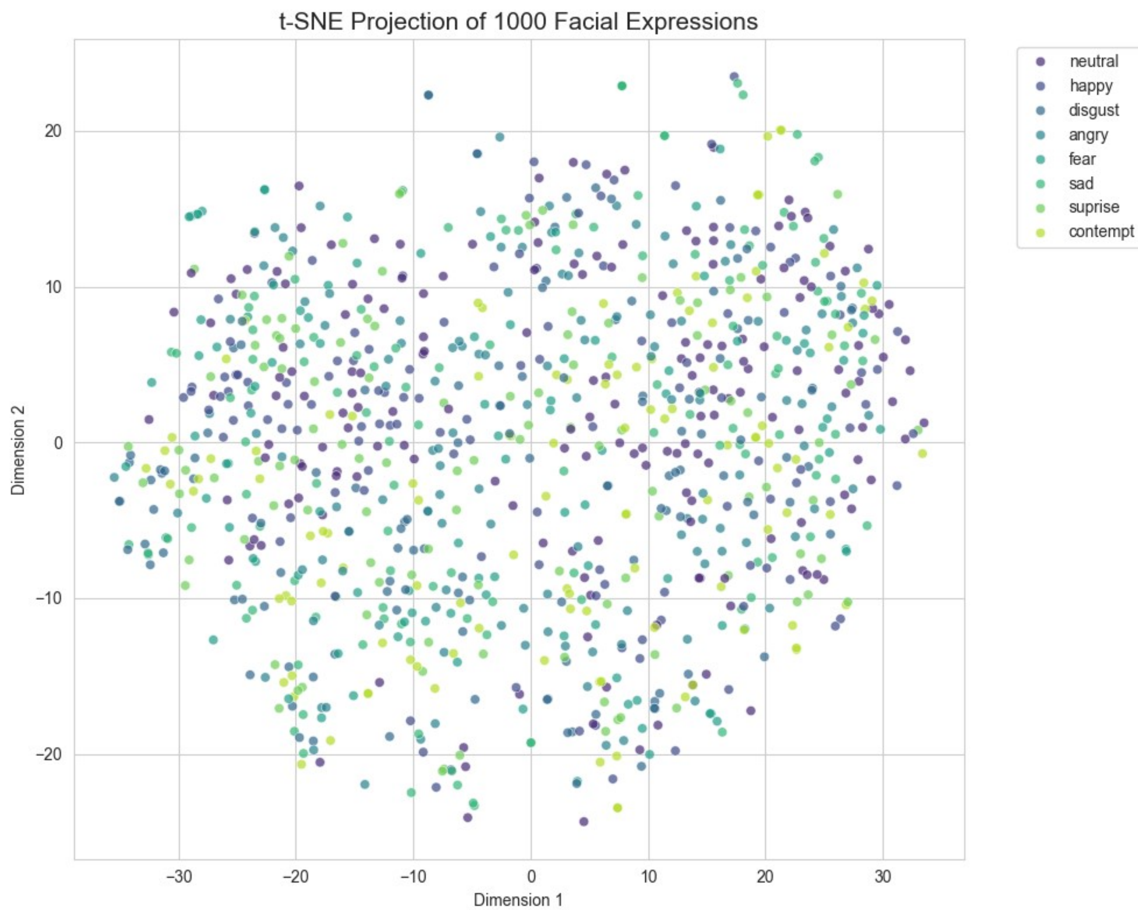
* **t-SNE Transformation**: It applies the t-SNE algorithm to reduce those 2,304

pixel dimensions down to just two (Dimension 1 and Dimension 2). t-SNE works by keeping similar images close together and pushing dissimilar images apart.

* **Visualization**: Finally, it creates a scatter plot where each point represents an image, colored according to its emotion label.

Purpose

The goal is to see how "separable" the emotions are based on raw pixel values. It helps us understand if certain emotions (like "**Angry**" and "**Disgust**") look very similar to the computer, which would make them harder for the AI to distinguish later.



.4 Edge Detection

Code Explanation

* **Automated Sampling**: The code identifies all unique emotions (labels) in the dataset and selects one random sample image for each category.

* **Dual Visualization**: It creates a grid with two rows:

  - **Row 1 (Original)**: Displays the raw grayscale facial images to provide a direct look at the data the model will "**see**."

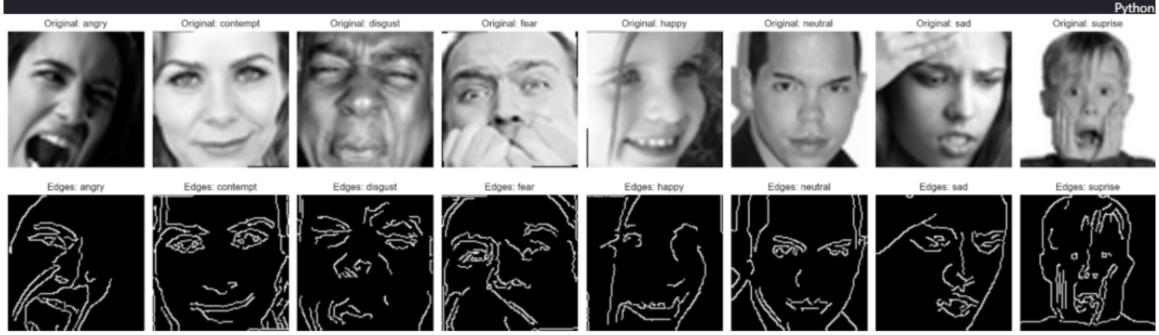
- **Row 2 (Canny Edge Detection)**: Applies the Canny Edge Detection algorithm to the same images. This mathematical operation identifies areas with sharp changes in intensity, effectively highlighting the outlines of facial features like eyes, eyebrows, and mouths.

* **Format**: It uses `**plt.subplots**` to align them perfectly for a side-by-side comparison across all emotion classes.

Purpose

This section is crucial for understanding feature extraction. Facial expressions are primarily defined by the movement of specific muscles (the "**edges**" of the mouth or eyes). By visualizing the edges, we can verify if the important structural information of an emotion is preserved after filtering out background noise and lighting variations. It helps confirm that the images are clear enough for a model to recognize specific facial contours.

```python
unique_labels = df['label'].unique()

fig, axes = plt.subplots(2, len(unique_labels), figsize=(20, 6))

for i, label in enumerate(unique_labels):
    sample_row = df[df['label'] == label].sample(1).iloc[0]
    path = os.path.join(IMAGE_DIR, sample_row['filename'])

    img = cv2.imread(path, 0)

    if img is not None:
        axes[0, i].imshow(img, cmap='gray')
        axes[0, i].set_title(f"Original: {label}")
        axes[0, i].axis('off')

        edges = cv2.Canny(img, 100, 200)
        axes[1, i].imshow(edges, cmap='gray')
        axes[1, i].set_title(f"Edges: {label}")
        axes[1, i].axis('off')

plt.tight_layout()
plt.show()
```
Python



5. Data Preprocessing & Engineering

To transform raw pixels into a format suitable for Deep Learning, we implemented the following pipeline:

-- **Normalization**: Pixel intensities were rescaled from [0, 255] to [0, 1] to optimize gradient descent.

-- **Feature Cleaning**: We addressed missing values and ensured all images followed the (48, 48, 1) tensor shape.

-- **Label Transformation**: Categorical labels were One-Hot encoded to facilitate multi-class cross-entropy calculation.

6. Advanced Data Augmentation

To prevent the model from memorizing the training set (Overfitting), we implemented a real-time augmentation layer. This effectively increases the dataset's diversity by simulating different camera angles and lighting conditions:

-- **Geometric Transforms**: Random rotations (15°), width/height shifts, and horizontal flips.

-- **Intensity Transforms**: Random zoom and brightness adjustments.

6.1. Image Brightness & Quality Assessment

The box plot analysis of average pixel intensities across different classes (Figure X) shows a relatively consistent distribution. Most emotions have a median brightness centered around 125-150.

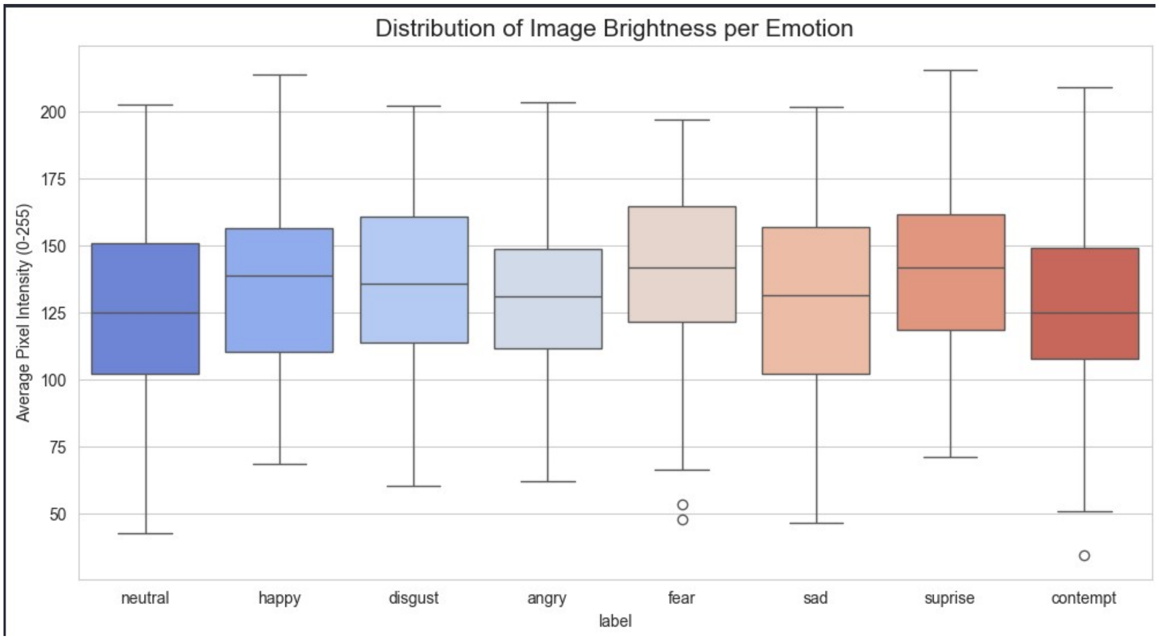
Conclusion: This consistency indicates that the dataset is well-balanced in terms of lighting conditions across different emotions. Consequently, the model is expected to focus on **facial morphology and landmarks** (like mouth and eye shapes) rather than being misled by environmental lighting or exposure differences. To further standardize this, a Global Normalization **[0, 1]** was applied during preprocessing.

Purpose

The goal is to determine if the lighting conditions are consistent across different emotion categories. In a robust dataset, "Happy" images shouldn't be significantly brighter than "Sad" images just because of the camera settings. If one category is much darker than others, the model might accidentally learn to associate "darkness" with that emotion rather than the actual facial features.

```python
brightness_data = []

subset_df = df.sample(1000, random_state=42)

for index, row in subset_df.iterrows():
    path = os.path.join(IMAGE_DIR, row['filename'])
    try:
        img = cv2.imread(path, 0)
        if img is not None:
            avg_brightness = img.mean()
            brightness_data.append({'label': row['label'], 'brightness': avg_brightness})
    except:
        pass

brightness_df = pd.DataFrame(brightness_data)

plt.figure(figsize=(12, 6))
sns.boxplot(data=brightness_df, x='label', y='brightness', hue='label', legend=False, palette='coolwarm')
plt.title('Distribution of Image Brightness per Emotion', fontsize=15)
plt.ylabel('Average Pixel Intensity (0-255)')
plt.show()
```

Python



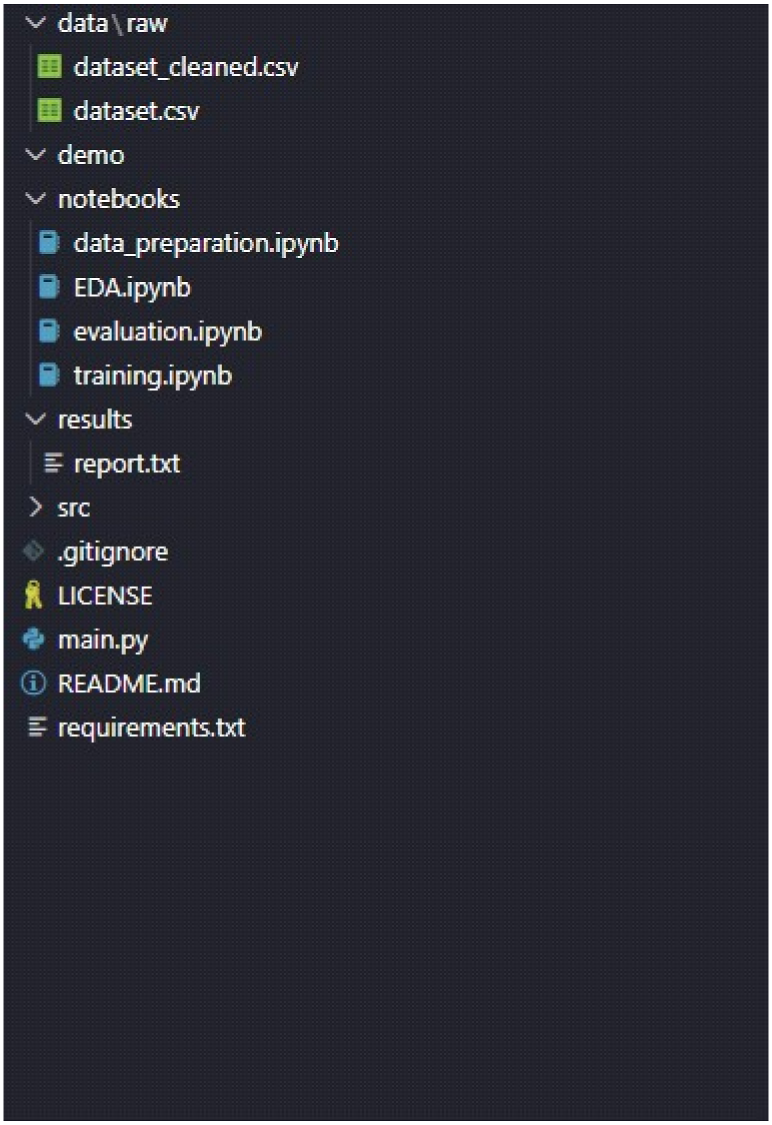
7. Architectural Design of the Baseline Model

Following the modularity requirements of the course, we designed a Convolutional Neural Network (CNN). The architecture consists of:

-- **Convolutional Blocks**: For hierarchical spatial feature extraction.

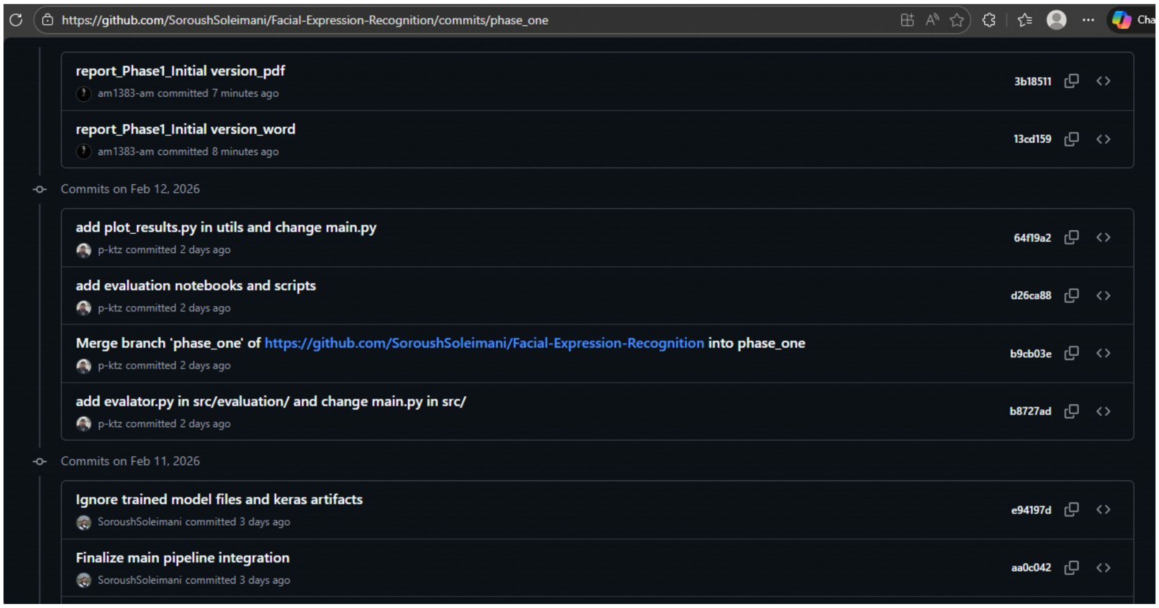
-- **Batch Normalization**: To stabilize the learning process.

-- **Dropout Layers**: To enhance the model's generalization capability.



6. GitHub Integration & Version Control

As part of our professional workflow, the project is maintained on GitHub with a modular structure. We used Git for collaborative development, ensuring all changes in preprocessing and model design are tracked through meaningful commits.



https://github.com/SoroushSoleimani/Facial-Expression-Recognition/commits/phase_one

report_Phase1_Initial version_pdf
am1383-am committed 7 minutes ago
3b18511

report_Phase1_Initial version_word
am1383-am committed 8 minutes ago
13cd159

Commits on Feb 12, 2026

add plot_results.py in utils and change main.py
p-ktz committed 2 days ago
64f19a2

add evaluation notebooks and scripts
p-ktz committed 2 days ago
d26ca88

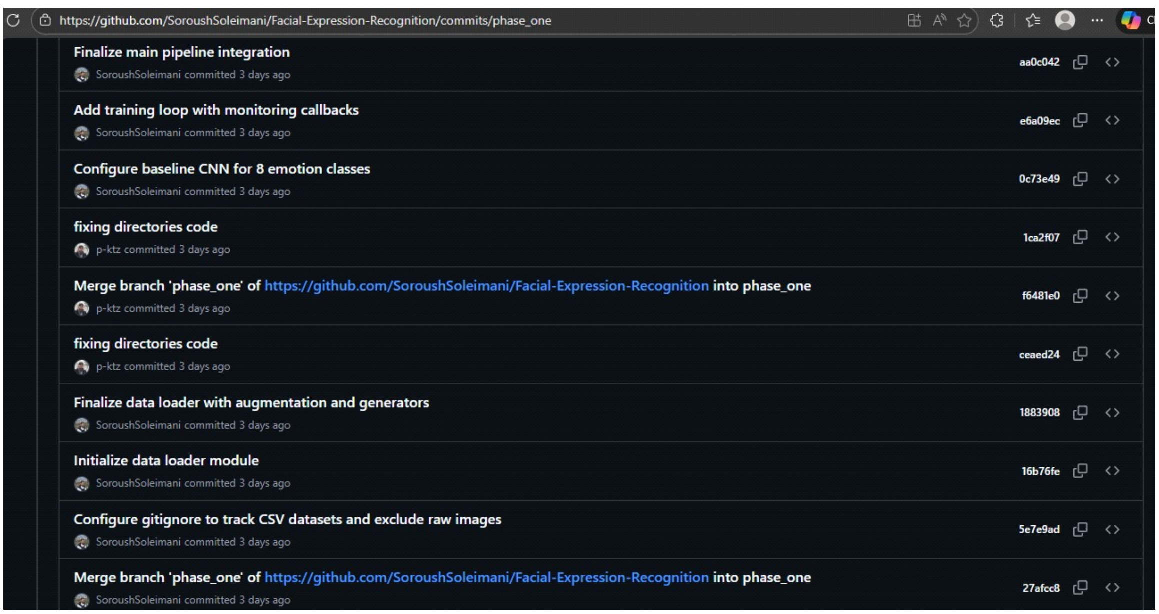
Merge branch 'phase_one' of https://github.com/SoroushSoleimani/Facial-Expression-Recognition into phase_one
p-ktz committed 2 days ago
b9cb03e

add evalator.py in src/evaluation/ and change main.py in src/
p-ktz committed 2 days ago
b8727ad

Commits on Feb 11, 2026

Ignore trained model files and keras artifacts
SoroushSoleimani committed 3 days ago
e94197d

Finalize main pipeline integration
SoroushSoleimani committed 3 days ago
aa0c042



https://github.com/SoroushSoleimani/Facial-Expression-Recognition/commits/phase_one

Finalize main pipeline integration
SoroushSoleimani committed 3 days ago
aa0c042

Add training loop with monitoring callbacks
SoroushSoleimani committed 3 days ago
e6a09ec

Configure baseline CNN for 8 emotion classes
SoroushSoleimani committed 3 days ago
0c73e49

fixing directories code
p-ktz committed 3 days ago
1ca2f07

Merge branch 'phase_one' of https://github.com/SoroushSoleimani/Facial-Expression-Recognition into phase_one
p-ktz committed 3 days ago
f6481e0

fixing directories code
p-ktz committed 3 days ago
ceaed24

Finalize data loader with augmentation and generators
SoroushSoleimani committed 3 days ago
1883908

Initialize data loader module
SoroushSoleimani committed 3 days ago
16b76fe

Configure gitignore to track CSV datasets and exclude raw images
SoroushSoleimani committed 3 days ago
5e7e9ad

Merge branch 'phase_one' of https://github.com/SoroushSoleimani/Facial-Expression-Recognition into phase_one
SoroushSoleimani committed 3 days ago
27afcc8