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

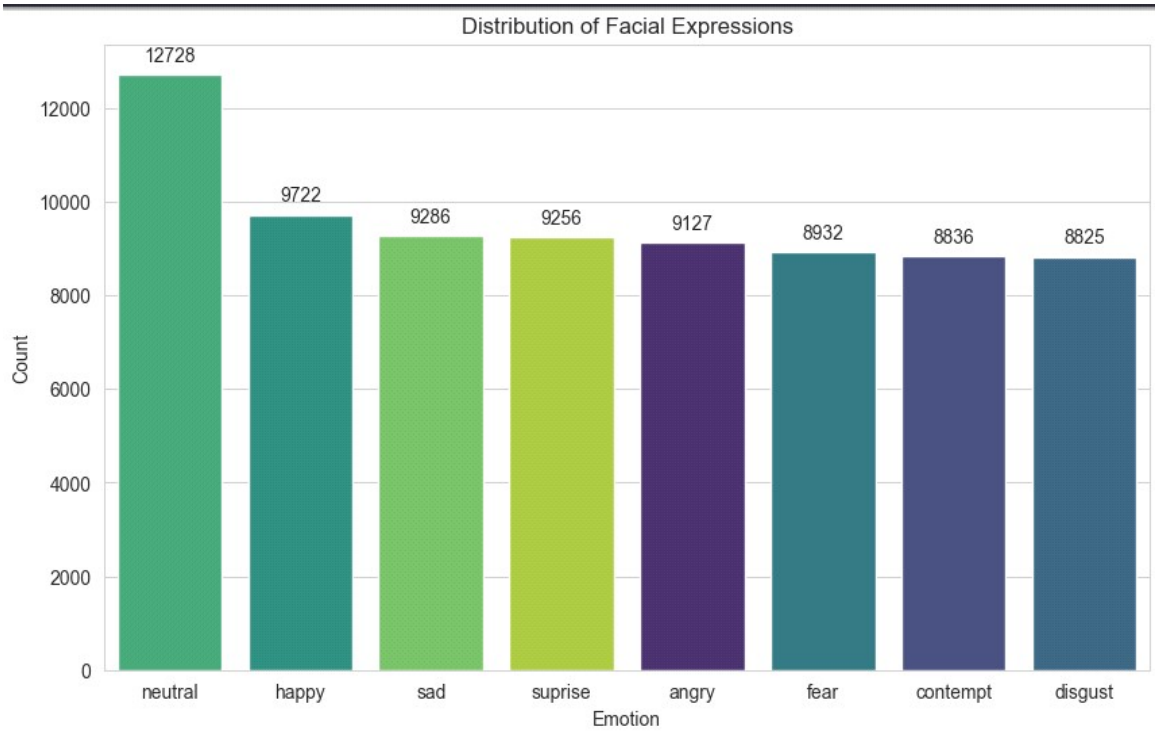
The core objective of this project is to develop a robust Computer Vision pipeline capable of classifying human emotions into seven distinct categories. Facial Expression Recognition (FER) is a pivotal task in Affective Computing, enabling machines to interpret human psychological states. Our system processes grayscale facial images to detect: **Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral**.

2. Dataset Selection & Exploratory Data Analysis (EDA)

We utilized the FER-2013 dataset, a benchmark in the field. Before model design, we conducted an extensive EDA to understand the data's underlying patterns.

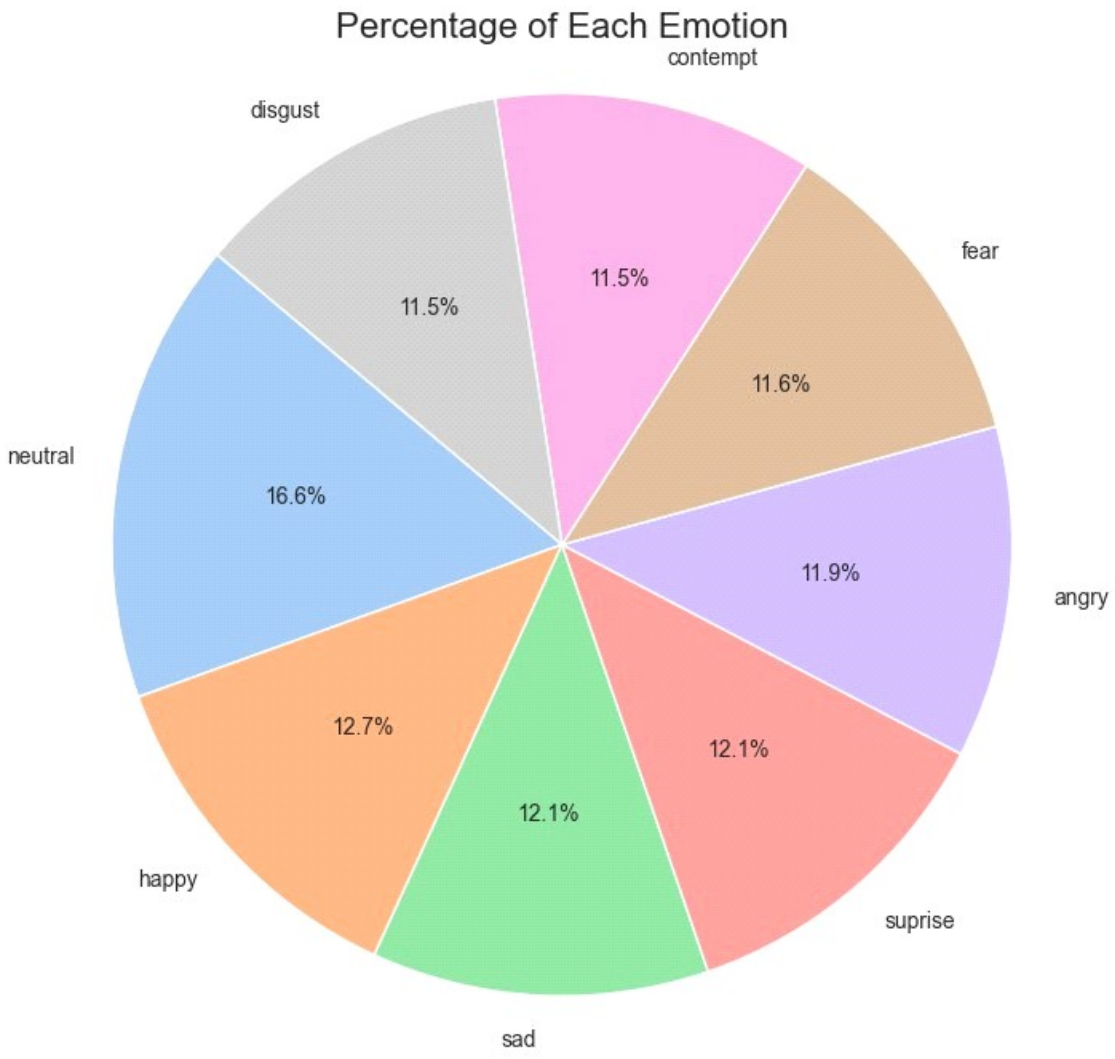
2.1. Class Imbalance Analysis

Our analysis revealed a significant variance in the number of samples per class. For instance, the 'Happy' class has a high density, while 'Disgust' is underrepresented. Recognizing this imbalance is crucial for selecting the appropriate loss function and augmentation strategy.



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.

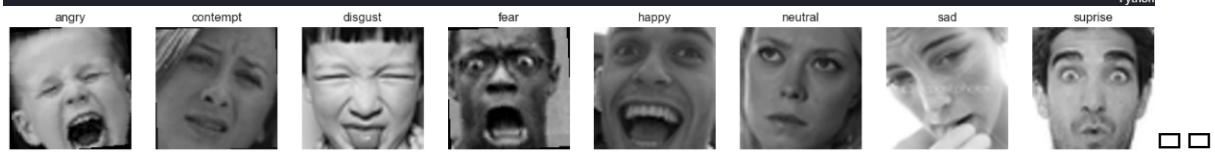


2.3. Visualizing Sample Images

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).

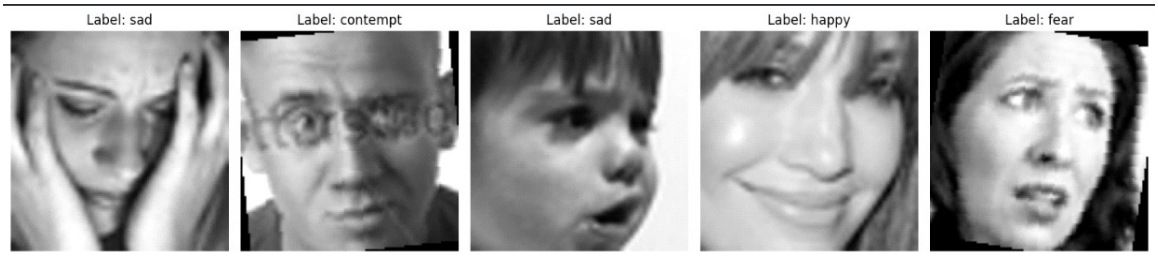
```python
IMAGE_DIR = "../data/raw"
unique_labels = df['label'].unique()

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()
```

Python



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.

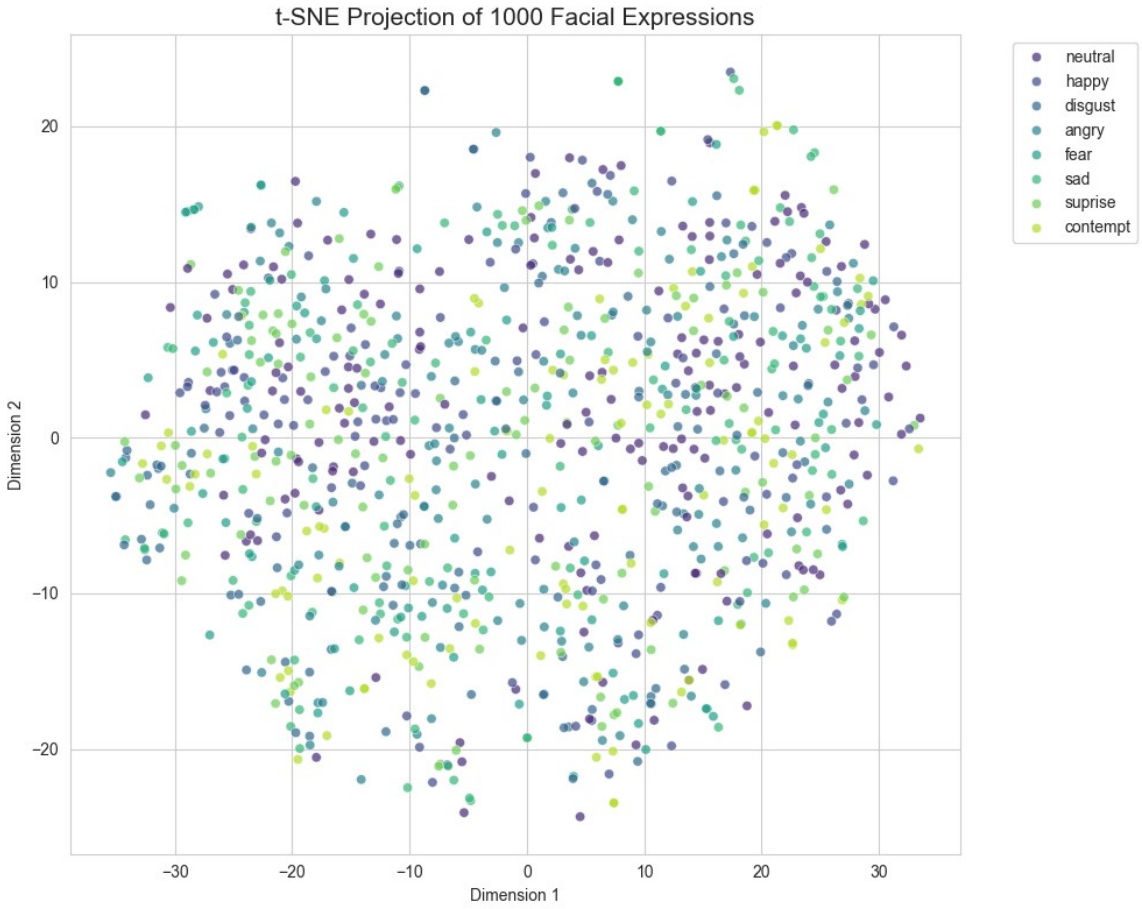
* **Preprocessing**: The code loops through the sampled images, converts them to grayscale, and resizes them to a uniform 48x48 resolution. It then flattens each image into a 1D array of pixels (2,304 features) so the mathematical model can process them.

* **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.

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.

4. 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.

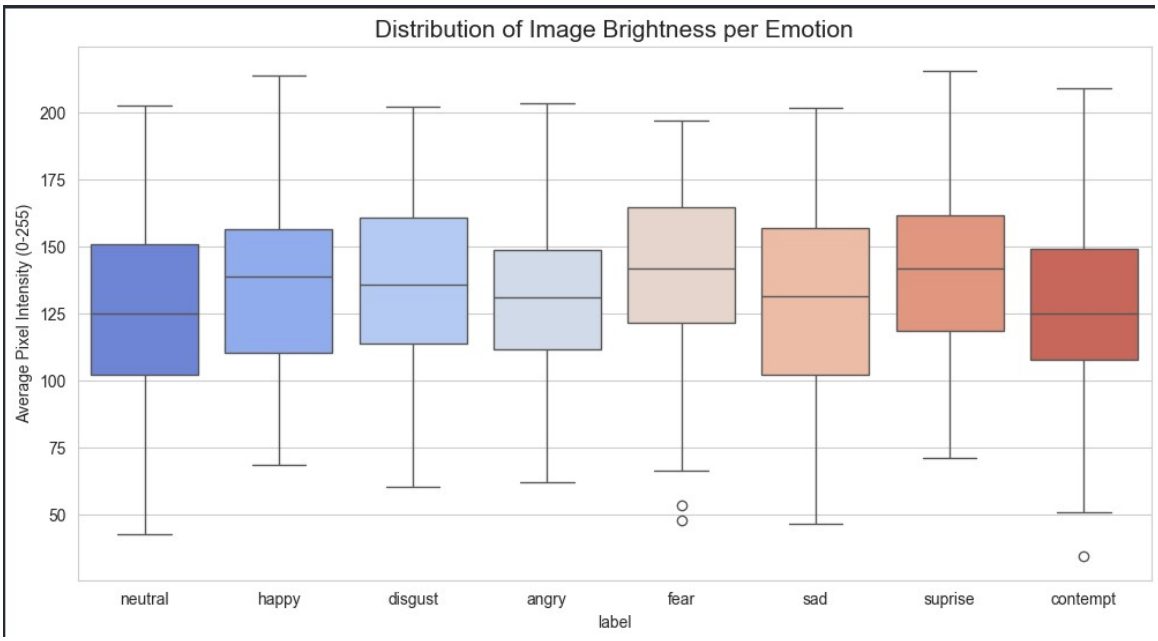
-- **Intensity Transforms**: Random zoom and brightness adjustments.

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



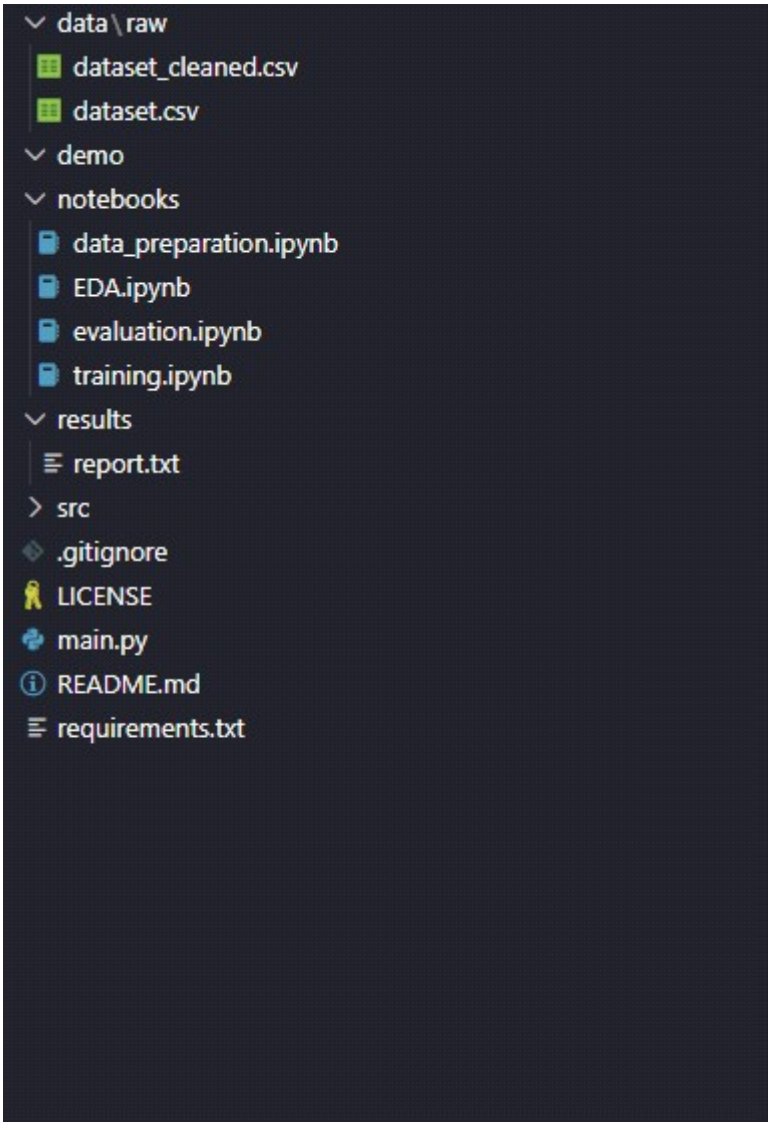
5. Architectural Design of the Baseline Model

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.

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