COMP 6721

Applied Artificial Intelligence

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Project Part 1: A.I.ducation Analytics

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Github- https://github.com/parthshah312/COMP-6721-Project.git

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Chapter 1: Dataset

- **Overview of Existing Dataset**

Total Number of Images: 2194

Numbers per Class:

Angry- 509

Bored- 557

Focused- 477

Neutral- 654

★ All the images in the dataset are mostly frontal face shots.

- **Justification for dataset choices**

The collection is unusual in that it includes conversational expressions, which are frequently disregarded in facial expression studies. The expressions are created using a method-acting process based on ordinary circumstances, which ensures both well-defined and natural face expressions.

The dataset gains credibility by the application of a method-acting procedure.

The dataset records more realistic and contextually relevant face reactions by connecting expressions to commonplace situations.

The dataset's adaptability is increased by the availability of expressions in various repetitions, intensities, and camera angles.

The database helps researchers in a variety of domains, such as perceptual and cognitive sciences, emotional computing, and computer vision.

Challenges that may be encountered include:

Subjectivity in Expression Interpretation: Assessing and validating face expressions can be subjective, especially in a dataset emphasizing naturalness. It may be difficult to get consensus among human annotators or to construct automated systems capable of precisely comprehending the intended statements.

Data Volume and Processing: Including dynamic expressions and varying repetitions, intensities, and camera angles may result in an increase in overall data volume. Managing and analyzing such a large dataset might be difficult, especially if computer resources are restricted.

Generalization Across Individuals: The dataset contains expressions from 19 different people. It may be necessary to ensure that findings generalize over a larger population. Individual variances in face expressions may have an influence on the project's capacity to draw general findings.

- **Provenance Information**

The whole dataset is uploaded on our project github repository and the images were mainly obtained from two different sources. [2], [3].

Chapter 2: Data Cleaning

- **Techniques**

    - For imperfect size images we resized images into one common sized image (48 x 48).
    - For light augmentation techniques we simply performed brightness enhancing and contrast enhancing on images, by using these techniques we enhanced our images to 50% more brighter.
    - For Reduced Dimensionality , by simplicity and Feature Extraction we simply converted every image into gray scale images.

- **Challenges:**

1. Varied Image Sizes and Resolutions:

Challenge: Images in the dataset had different sizes and resolutions.
Solution: Standardizing the dataset by resizing images to a common dimension.

2. Inconsistent Lighting Conditions:

Challenge: Some images had diverse lighting conditions, affecting the visibility of facial features.
Solution: Brightness adjustments, contrast normalization.

3. Noisy or Mislabelled Data:

Challenge: Some images in the dataset were mislabelled.
Solution: Manually reviewing and correcting mislabelled images.

4. Class Imbalance:

Challenge: The number of images per class were slightly uneven.

Solution: Added more images for that particular class

5. Limited Diversity in Expressions:

Challenge: The dataset lacks diversity in facial expressions, particularly for specific classes.

Solution: Actively seeking and including images that represent a wide range of expressions for each class.

Chapter 3: Labeling

- **Methods And Platforms:**

  First we carefully analyze each and every image of the dataset and put each and every image manually into different types of emotion classes.

  For data labeling, we first load each image with appropriate emotion labels and store it into a labeled list.

  One-hot Encoding: Using this method, we converted each labeled data into binary vectors.

  For example : in our project we detect 4 type of emotions (angry,bored,neutreal,bored) so, by one hot encoding these labeled class look like,

  Angry [1,0,0,0]

  Bored [0,1,0,0]

  Neutral [0,0,1,0]

  Bored [0,0,0,1]

Challenges faced when merging dataset:

1. Label Consistency:

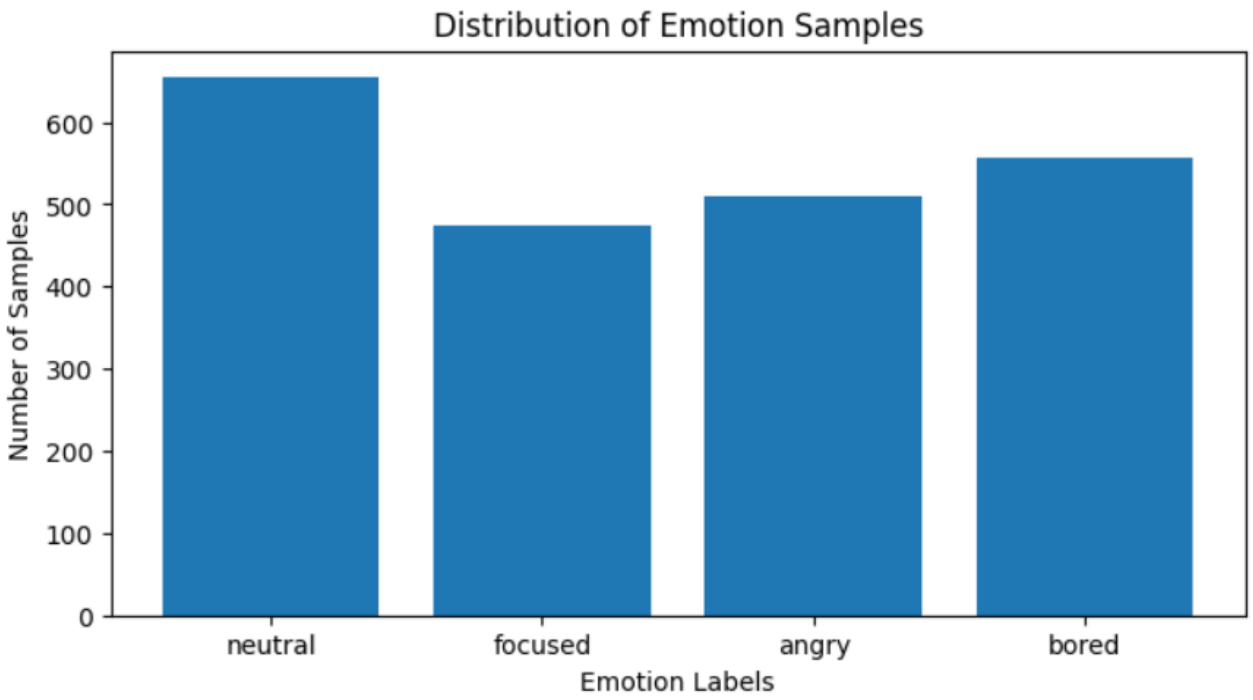
   Challenge: Different naming conventions were used across different dataset.
   Solution: We manually adjust labels to make them consistent.

2. Data Quality:

   Challenge: Datasets had varying levels of image quality.
   Solution: We removed low quality images.

Chapter 4: Data Visualization

- **Class Distribution:**



Bar Graph: A bar graph is used to visualize the count of images in each class. Each bar represents a facial expression class, and the height of the bar corresponds to the number of images in that class.

Labels: Each bar is labeled with the corresponding class name for clarity.

Imbalance Check: Analyze if certain classes are overrepresented or underrepresented. A balanced distribution helps in training machine learning models more effectively.

We have displayed a bar graph showing the number of images for each class. Labeled each bar with the corresponding class name. We have also analyzed for a nearly equal distribution of classes.

- **<u>Sample Images:</u>** Provide a visual representation of the dataset's content through a set of randomly selected images.

  Purpose: Identify anomalies, ensure diversity in samples, and visually inspect the variety of facial expressions within each class.

  Grid Layout: A 5x5 grid is used to display a collection of 25 images, with each row representing a different class.

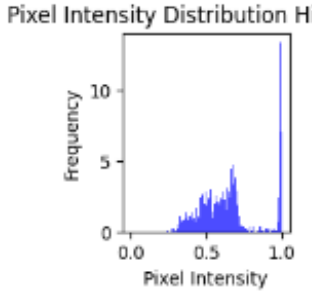
  Random Selection: Images are randomly chosen from each class to ensure a representative sample.

  Each image is labeled with its corresponding class to aid interpretation.

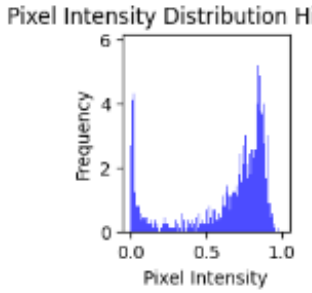
<u>Pixel Intensity Distribution:</u> Understand the distribution of pixel intensities in images, providing insights into lighting conditions. Assess potential challenges related to image quality, such as variations in lighting conditions.

Histogram: A histogram is plotted to visualize the distribution of pixel intensities in a set of random images.

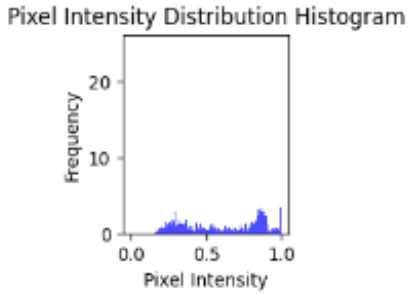
Emotion: angry



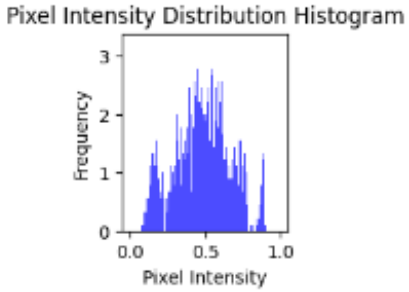
Emotion: bored



Emotion: neutral

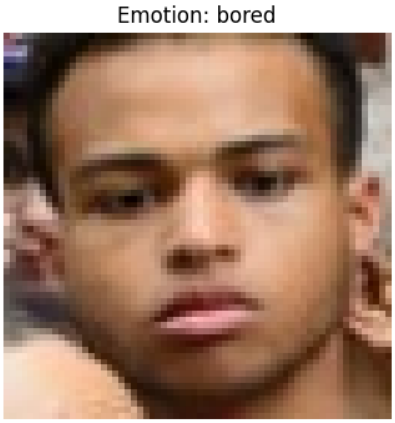


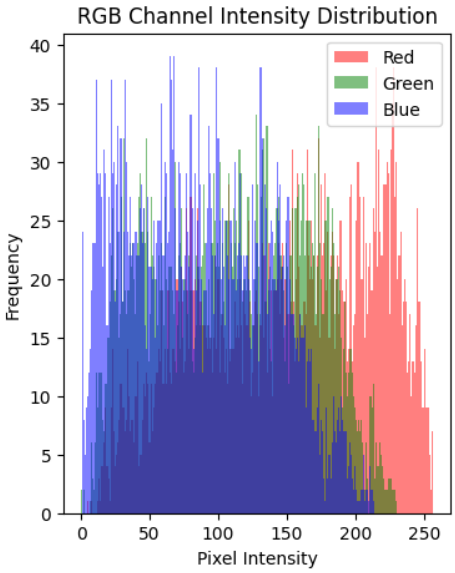
Emotion: focused



- **<u>RGB colored image intensity Distribution:</u>** Working with color images, overlay histograms for the Red, Green, and Blue channels on a single plot. This provides insights into color variations.

  Frequency vs. Intensity: The x-axis represents pixel intensity, and the y-axis represents the frequency of pixels at each intensity level.





References

[1] Kaulard K, Cunningham DW, Bülthoff HH, Wallraven C (2012),"The MPI Facial Expression Database — A Validated Database of Emotional and Conversational Facial Expressions," PLoS ONE 7(3): e32321.
Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0032321

[2] Facial-Expression-Classification-Dataset(3Classes) dataset for Facial Recognition(FER-2013 dataset; accessed October 24, 2023).
https://www.kaggle.com/datasets/nightfury007/fercustomdataset-3classes

[3] The large MPI Facial Expression- A Validated Database of Emotional and Conversational Facial Expressions(MPI dataset; accessed October 25, 2023)
https://www.b-tu.de/en/graphic-systems/databases/the-large-mpi-facial-expression-database