Gina Cody School of Engineering and Computer Science

COMP 6721 Applied Artificial Intelligence (Fall 2023)

Project Assignment, Part I

Submitted To: Professor **Dr. René Witte**

Submitted By:

Team Name	**NS_14**	
Student Name	**ID**	**Specialization**
Anurag Agarwal	40232644	Data Specialist
Vidhi Sagathiya	40232374	Training Specialist
Jimi Mehta	40225526	Evaluation Specialist

We certify that this submission is the original work of members of the group and meets the Faculty's Expectations of Originality

GitHub Repository: ***AIDucation Analytics***

Dataset

We have incorporated the "AffectNet Training Data" dataset, sourced from Kaggle, as part of our project. This dataset contains facial images with associated emotions. Here is an overview of this dataset:

Overview

AffectNet is a large database of faces labeled by "affects" (psychological term for facial expressions). To accommodate common memory constraints, the resolution was reduced to 96x96. Meaning that all images are exactly 96x96 pixels.

Total Images	**2465**
Class Name	**Number of Images**
Anger	790
Engaged/ Focused	503
Bored/ Tired	500
Neutral	672

Characteristics of Dataset

The "AffectNet Training Data" dataset is notable for its diverse collection of facial expressions and emotions. It encompasses a wide range of emotions, including happiness, sadness, anger, and neutrality, making it a comprehensive resource for emotion recognition tasks. The dataset features images with varying backgrounds, lighting conditions, and poses, providing a realistic representation of facial expressions in different real-world scenarios. It includes both frontal face shots and images with varying head orientations, enhancing its suitability for training AI models to recognize emotions in diverse contexts. This diversity in emotions and environmental factors makes the dataset an asset for building robust and versatile facial emotion recognition systems.

Justification for Dataset Choices

In the pursuit of developing an effective AI system for emotion recognition and object classification, the selection of appropriate datasets plays a pivotal role in the success of the project. The dataset chosen for this project has been carefully selected based on its relevance, diversity, and the challenges it may present. This section provides a detailed justification for the dataset choice.

The "AffectNet Training Data" dataset from Kaggle was a natural choice for our project due to its close alignment with our primary task of emotion recognition. This dataset offers a substantial collection of facial images, each labeled with a specific emotion [1].

The relevance of this dataset to our project is evident as it provides a comprehensive range of emotions, including happiness, sadness, anger, and neutrality, among others [1]. The substantial size of this dataset, with 15000 images, ensures that our AI model has access to a rich variety of emotional expressions, making it ideal for training a robust emotion recognition system [1].

Also, by using Singular Value Decomposition, each image's Principal Component Analysis was calculated. The threshold for the "percentage of the first component (index 0) in the principal components" (in short, the PFC%) was set to lower than 90%. This means that most if not all the monochromatic images were filtered out.

Challenges faced

Challenges posed by the "AffectNet Training Data" dataset primarily include data diversity, data management and class imbalance.

Data Diversity: The dataset's diversity in terms of lighting conditions, facial orientations, and backgrounds presented challenges. Variability in real-world conditions can affect the model's ability to generalize. Strategies to ensure the model's robustness across diverse scenarios were necessary.

Data Management: The dataset is substantial, containing many images. Managing and processing this volume of data efficiently was a significant challenge. Effective data preprocessing techniques were essential to ensure the dataset was well-prepared for model training.

Class Imbalance: An inherent challenge in emotion recognition tasks is class imbalance. In our dataset, some emotions were more common than others, which could potentially bias the model's performance. It was crucial to address this imbalance to ensure the accurate recognition of all emotions.

Provenance Information

The table below details the sources of each image (or image batch) used in our dataset. It includes relevant information such as source links, licensing types, and additional details where applicable:

Dataset Name	Source	License	Date of Download
Fer Affectnet Database	Kaggle	Attribution-NonCommercial-ShareAlike 3.0 IGO (CC BY-NC-SA 3.0 IGO)	October 20, 2023

Data Cleaning

Data cleaning is a critical step in preparing our dataset for training and testing our AI model. It involves standardizing the dataset by ensuring consistent image dimensions and quality. This section outlines the techniques and methods applied for data cleaning, the encountered challenges, and provides illustrative examples to substantiate the impact of these cleaning processes.

1. Resizing Images

The first step in data cleaning involved resizing the images to a uniform dimension. Standardizing the image size is essential for consistency and efficient processing. Initially, we considered resizing the images to a uniform dimension as part of the data cleaning process. However, upon closer examination, we found that the images in our dataset already had an optimal size.

Rationale for Not Resizing:

*Optimal Size***:** The images in the "AffectNet Training Data" dataset were inherently of the dimension 96x96 pixels. This size is widely used for training deep learning models, and it was well-suited for our project's requirements [1].

*Avoiding Distortion***:** Resizing images can lead to aspect ratio distortion. Images may appear stretched or compressed, which can adversely affect the quality and interpretability of the dataset [2].

By retaining the original image size, we avoided unnecessary alterations that could potentially compromise the dataset's integrity. This decision was aligned with the principle of preserving the quality and authenticity of the data [2].

Challenges: Since we opted not to resize the images, we did not encounter the aspect ratio distortion challenges typically associated with resizing [2].

2. Sorting and Filtering

1. *Sorting:* We initiated the data cleaning process by sorting the dataset based on class labels. This step was crucial in structuring the data for subsequent analysis and model training. It facilitated the efficient identification of how images were distributed across different emotion classes.

2. *Filtering:* To address class imbalance, we implemented a filter to ensure that each class contained a fixed number of images. For example, in a dataset with four classes, we aimed for an equal number of images from each class. This was particularly important in datasets like the "AffectNet Training Data," where some emotions were more prevalent than others.

Challenges: The primary challenges in this process were,

Determining the Fixed Number of Images: Deciding on the appropriate fixed number of images per class required careful consideration. We needed to strike a balance that allowed the model to train effectively without introducing excessive class imbalance.

Handling Imbalanced Distributions: Some datasets, such as the "AffectNet Training Data," exhibited imbalanced class distributions. This required special attention to ensure fair representation for all emotion categories.

Addressing Challenges: To overcome these challenges, we employed the following strategies:

Experimentation-Based Approach: The determination of the fixed number of images per class was guided by experimentation. We aimed to strike a balance that was representative of each class while providing an adequate amount of data for model training.

Resampling Techniques: In cases where certain emotion classes were underrepresented, we employed resampling techniques, including oversampling and under sampling, to create a balanced distribution. This approach ensured that our model had an equitable opportunity to learn from all emotion categories [3].

3. Manual File Deletion:

Manual Inspection: Following the filtering process, we engaged in manual inspection. In this step, a human reviewer examined each image individually to determine its relevance. The reviewer compared each file against the predefined criteria for inclusion or exclusion.

Deletion: Images that did not meet the inclusion criteria were deleted from the dataset. It was essential to have a backup of the dataset or a version control system in place to recover accidentally deleted files.

During the manual file deletion process, several decisions were made to determine which files should be retained and which should be deleted. These decisions were guided by predefined criteria and aimed to ensure that the dataset was clean, balanced, and relevant for training the AI model. Below are the key decisions taken during the deletion of files:

1. *Relevance to Target Classes:* The primary criterion for retaining or deleting a file was its relevance to the target classes. If an image did not clearly belong to any of the defined classes (Neutral, Engaged/Focused, Bored/Tired, and Angry), it was marked for deletion. This ensured that the dataset consisted only of images that could be categorized into one of these classes.
2. *Image Quality:* Images with poor quality, such as those with significant blurriness or artifacts, were candidates for deletion. Low-quality images could introduce noise and potentially mislead the model during training. High-quality, clear images were prioritized to improve model performance.
3. *Ambiguity:* Images with ambiguous or unclear facial expressions that could not be confidently categorized into any of the target classes were deleted. Ambiguous images could introduce uncertainty into the model's training process.

a. These images were deleted because of poor quality

Labeling:

In this section, we will describe how we arrived at the labels for our dataset, including the methods and tools used for labeling. We will also discuss any ambiguities encountered during the labeling process and how decisions were made to resolve them.

Methods and Tools Used for Labeling:

To label our dataset, we employed a systematic approach using Python scripting. The process involved the following steps:

1. *Image File Naming*: All the images in our dataset were named in a consistent format, which included a serial number as part of the file name. For example, the naming convention followed was "image_number.jpg," where "number" represented a unique serial identifier.
2. *Labeling Script*: We created a Python script that scanned the image file names and extracted the serial number to determine the class label for each image. The script utilized this serial number to automatically assign the appropriate class label. For instance, if the serial number indicated an image of an engaged student, the script assigned the "Engaged" label to that image.
3. *CSV File Creation*: As a result of the labeling script, a CSV (Comma-Separated Values) file was generated. This CSV file included two columns: one for the file path and another for the corresponding class label. The file path represented the location of each image in the dataset, while the class label indicated the category to which the image belonged (e.g., Neutral, Engaged, Bored/Tired, or Angry).

Ambiguities Encountered and Resolution:

During the labeling process, we encountered minimal ambiguities due to the structured and consistent naming convention of the image files. However, in cases where ambiguities did arise, they were typically related to file extensions. Some images in the dataset had a ".png" file extension, while the labeling process assumed ".jpg" extensions.

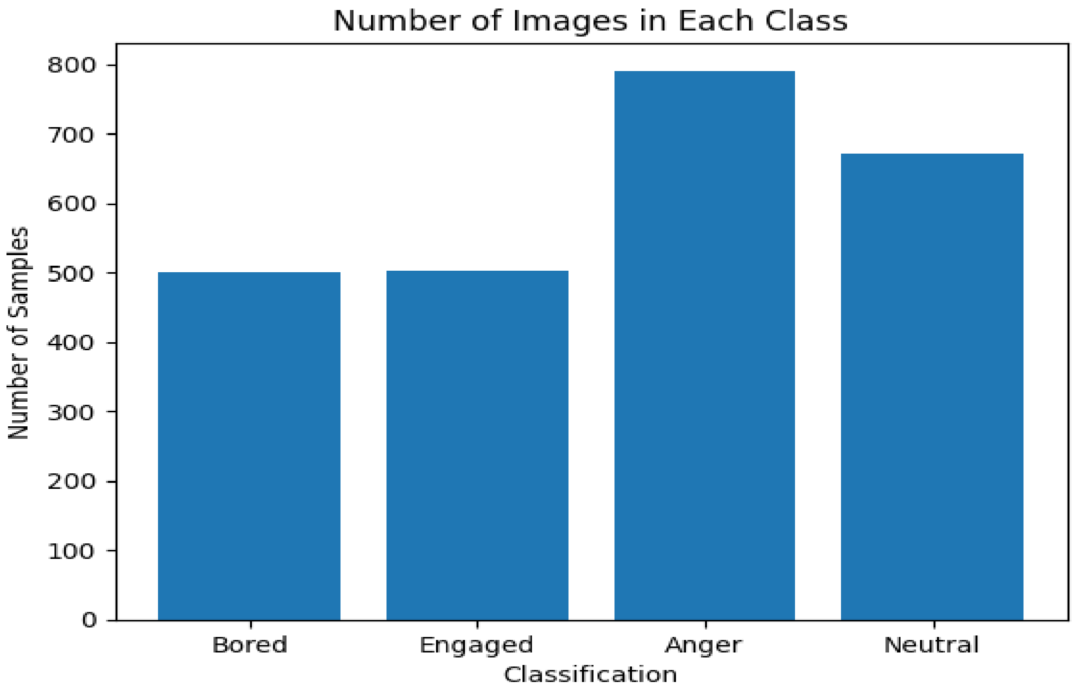
To address this issue, we implemented a Python code snippet to convert the file extensions from ".png" to ".jpg." This ensured uniformity in file extensions and allowed the labeling script to function correctly without ambiguities.

The use of Python scripting and the structured file naming convention contributed to a streamlined and efficient labeling process. Any potential ambiguities related to file extensions were resolved by converting all image file extensions to ".jpg," ensuring that the labeling process was consistent and accurate. The resulting CSV file contained the necessary information for each image, enabling seamless integration into our AI-driven educational analytics project.

Dataset Visualization

Visualizing the quantity of samples in each class is crucial for comprehending the data distribution across the various classes for the project. Results from an unequal distribution may be skewed since the model may have good performance when predicting overrepresented classes but poor performance while predicting underrepresented ones.

Bar graph: To comprehend the distribution of data across different classes, we created a bar graph.



The number of samples would be shown by the y-axis, and the various classifications of emotions would be represented by the x-axis.This visualization displays the number of images in each class, making it easy to identify whether any class is overrepresented or underrepresented. This information is crucial as it can impact the model's performance.

Sample Images

To understand the type of data we're dealing with and catch any inconsistencies or labeling issues, visualization of random samples from the dataset is done.

5 x 5 image grid: 25 images at once in a 5 x 5 grid are displayed. Sampling images at random from different classes assures a distinct view with every program execution.

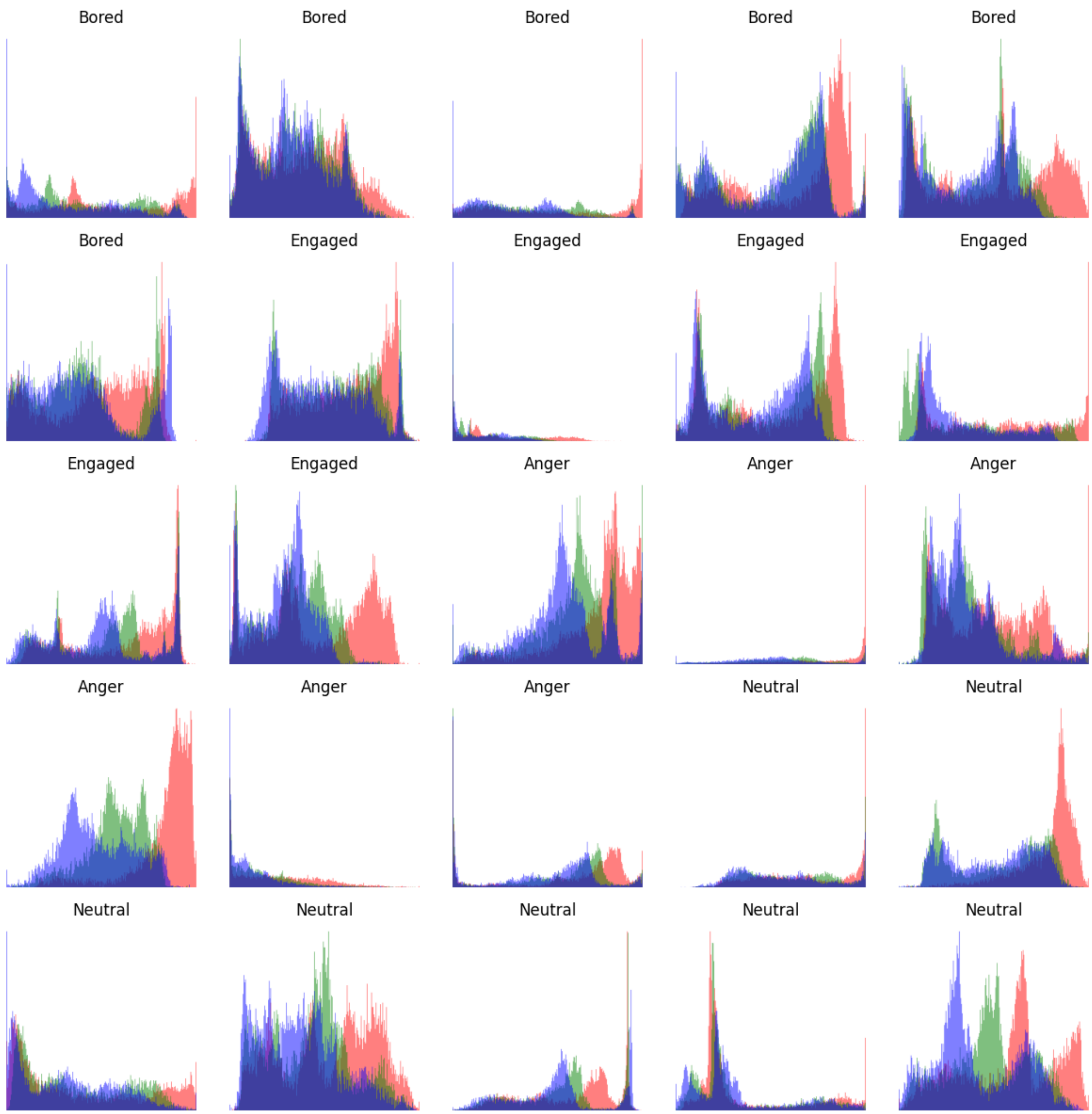
5 x 5 image grid:

Pixel Intensity Distribution:

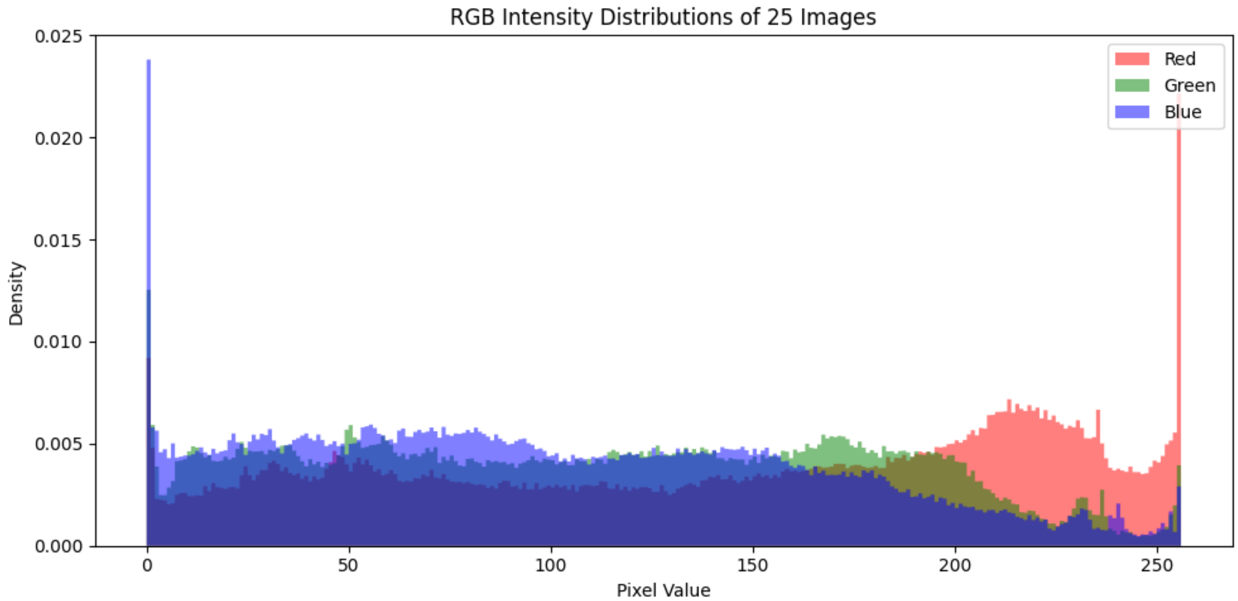
The below representation of pixel intensity graph comprehends the light and color distribution differences in the images. The original dataset did not require data enhancement or preprocessing operations like standardization due to good quality bright images in pixel intensities.

The first image represents Pixel intensity of each image picked in 25x25 grid is the previously picked sample. The second image represents the average Pixel Intensity Distribution of all the 25 images. Superimposition of the Red, Green, and blue channel histograms on top of RGB images is done in this step.

5 x 5 image grid Pixel Intensity Distribution with RGB:



RGB Intensity Distribution of 25 sample images:



In summary, these visualizations are essential for understanding the dataset's class distribution, content, and pixel intensity characteristics. They lay the foundation for making informed decisions when working with the data and building machine learning models.

References:

1. [1] AffectNet Dataset: Mollahosseini, A., Chan, D., Mahoor, M. H., & Mori, G. (2017). AffectNet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW).
2. Kaggle: Kaggle. (2023). Kaggle: Your Machine Learning and Data Science Community. Retrieved from https://www.kaggle.com
3. [2] Aspect Ratio Distortion: Jolliffe, I. T. (2002). Principal Component Analysis (2nd ed.). Springer.
4. [3] Resampling Techniques: Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. Journal of Artificial Intelligence Research, 16, 321-357.