



COMP 6721

Applied Artificial Intelligence

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Project Part 1 & 2: A.I.education 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: 2084

Numbers per Class:

Angry- 507

Bored- 501

Focused- 500

Neutral- 576

- ★ 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 mislabeled.

Solution: Manually reviewing and correcting mislabeled 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, neutral, 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.

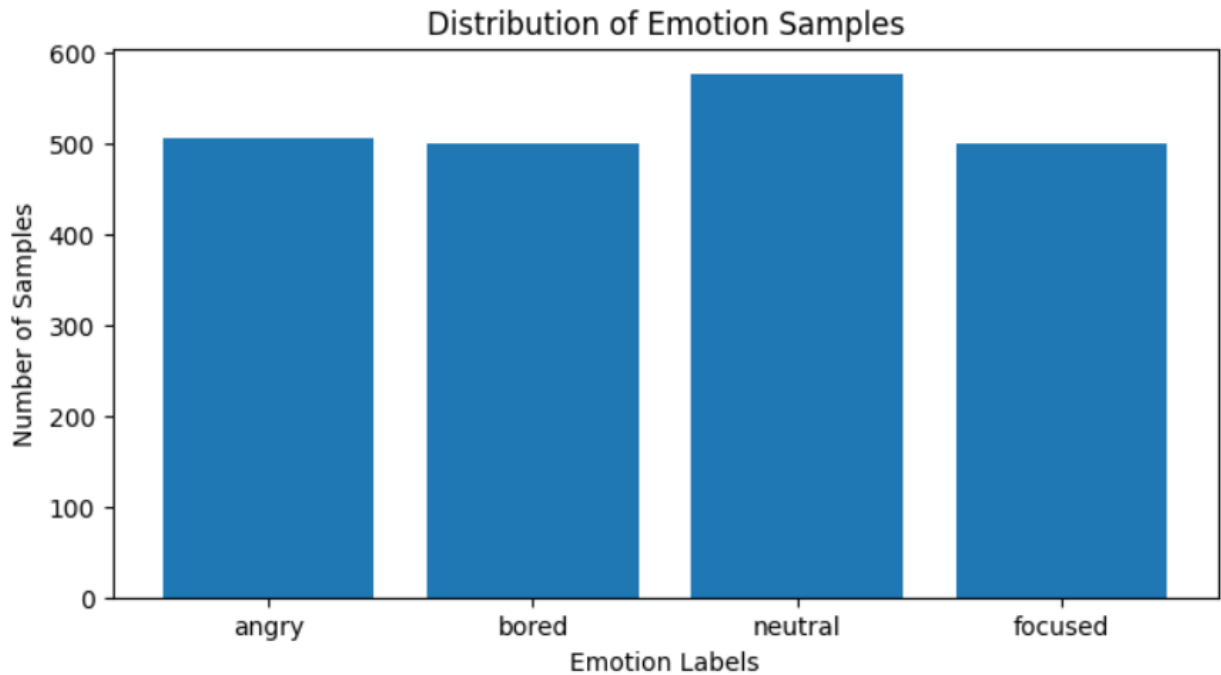
2. Data Quality:

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.

- **Sample Images:** 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.

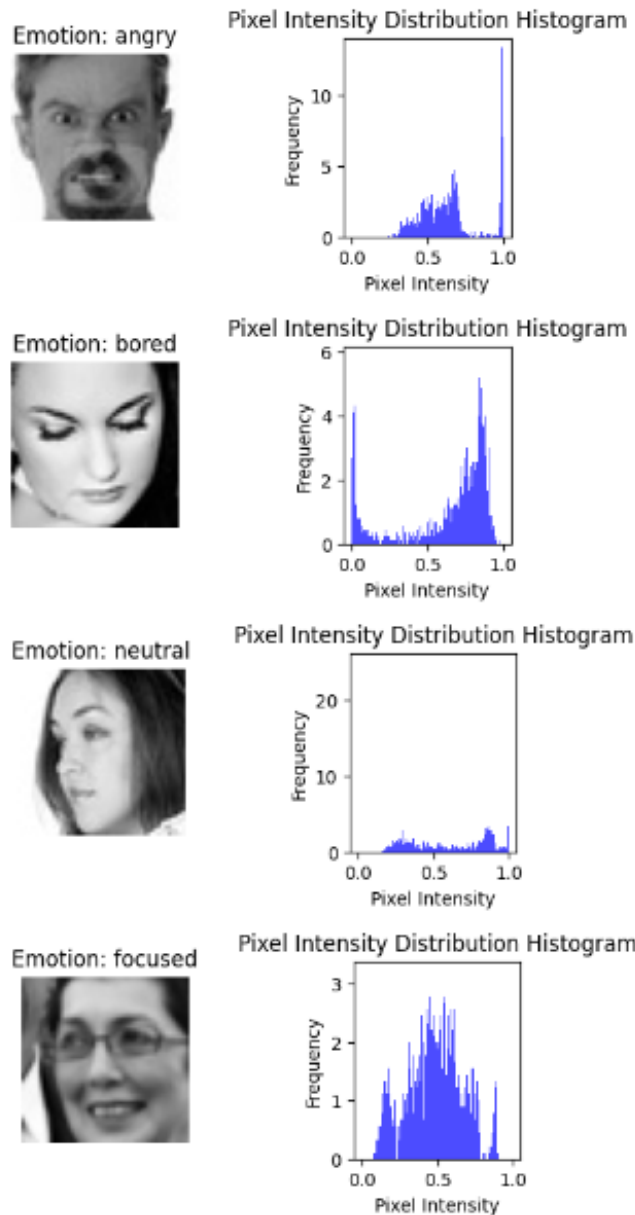
Random Selection: Images are randomly chosen from each class to ensure a representative sample.

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



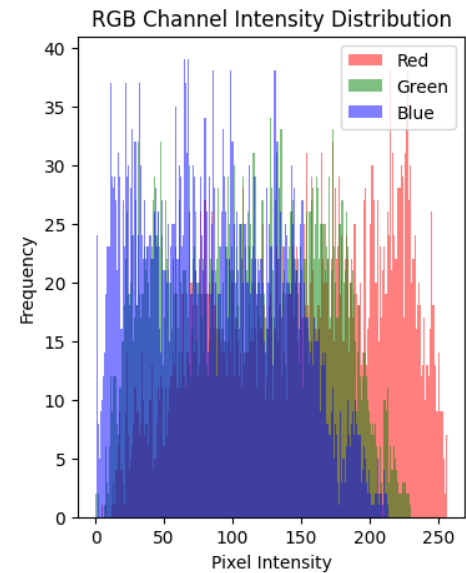
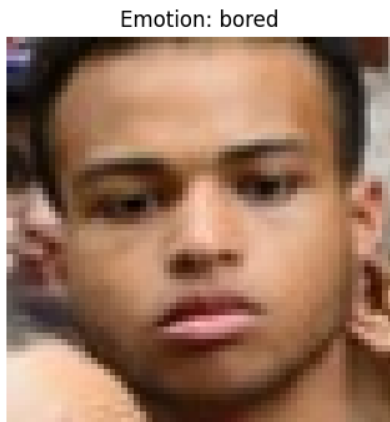
Pixel Intensity Distribution: Understand the distribution of pixel intensities in images, providing insights into lighting conditions. Assess potential challenges related to image quality, such as variations in lighting conditions.

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



- **RGB colored image intensity Distribution:** 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.



Chapter 5: CNN Architecture

1. Model Overview and Architecture Details:

When it comes to "A.I.education Analytics," a strong Convolutional Neural Network (CNN) is essential. To maximize its performance, our primary model is built with meticulous consideration for architectural elements and subtle design details. Let's examine our CNN architecture in more detail, including its layers, activation functions, and special features. We'll also look at the two versions that were added during the experimental stage.

Activation functions and layers:

Three convolutional layers and three fully linked layers make up our primary model. A 3 x 3 kernel size with a padding of 1 and a stride of 1 is used in each convolutional layer. Leaky ReLU is the activation function that we have selected for our model; it introduces non-linearity and permits the propagation of modest negative values.

Layer 1:

The first layer is the Convolution layer with kernel size 3 X 3 and padding 1. It produces 1 input channel and output with 64 channels.

Layer 2:

Convolution layer with 64 input channels, 128 output channels and kernel size 3 X 3 with padding 1.

Layer 3:

Convolution layer with 128 input channels, 256 output channels and kernel size 3 X 3 with padding 1.

Architectural Components:

Two dropout layers are positioned thoughtfully in our architecture to serve as a regularization strategy during training and prevent overfitting. To down sample the spatial dimensions and lower computational complexity while maintaining critical information, MaxPooling layers are integrated as pooling layers. We have used MaxPooling with Kernel size 2 and stride 2.

Fully Connected Layer 1:

The Hidden Layer contains 9216 neurons, and output layer contains 1024.

Fully Connected Layer 2:

The Hidden Layer contains 1024 neurons, and output layer contains 512.

Fully Connected Layer 3:

The Hidden Layer contains 512 neurons, and output layer contains 4.

Design Nuances:

We took great care to balance efficiency and complexity in our model's architecture. Convolutional and fully linked layers are used in this way to allow for the learning of hierarchical features, ranging from simple edges and textures to intricate facial structures. The Leaky ReLU activation function enhances the flexibility of the model's feature extraction procedure by allowing it to accommodate negative values.

2. Variant 1:

VGG19 Architecture: We chose the well-known VGG19 architecture for our initial variant. With three fully connected layers and five convolutional layers, this version presents a deeper network. The use of VGG19 is intended to investigate how deeper water affects the model's realism in capturing fine-grained facial characteristics. This form adds two dropout layers and preserves the ReLU activation function, providing a deeper comprehension of face features.

Convolution Layers:

Layer 1:

The first layer is the Convolution layer with kernel size 3 with padding 1. It produces 1 input channel and output with 64 channels.

Layer 2:

Convolution layer with 64 input channels, 128 output channels and kernel size 3 with padding 1.

Layer 3:

Convolution layer with 128 input channels, 256 output channels and kernel size 3 with padding 1.

Layer 4:

Convolution layer with 256 input channels, 512 output channels and kernel size 3 with padding 1.

Layer 5:

Convolution layer with 512 input channels, 512 output channels and kernel size 3 with padding 1.

Fully Connected Layer 1:

The Hidden Layer contains 25088 neurons, and output layer contains 4096.

Fully Connected Layer 2:

The Hidden Layer contains 4096 neurons, and output layer contains 4096.

Fully Connected Layer 3:

The Hidden Layer contains 4096 neurons, and output layer contains 4.

3. Variant 2:

Expanded Kernel Size: In this version, we extended the kernel size by choosing a 5 x 5 arrangement. The goal of this architectural modification is to evaluate the trade-offs between computational expense and geographical granularity. The model is anticipated to prioritize the recognition of larger facial features over finer details by increasing the kernel size. At the evaluation stage, a thorough analysis of the influence of this modification on the model's recognition capabilities will be conducted.

Convolutional Layers:

Layer 1:

The first layer is the Convolution layer with kernel size 5 X 5 and padding 1. It produces 1 input channel and output with 64 channels.

Layer 2:

Convolution layer with 64 input channels, 128 output channels and kernel size 5 X 5 with padding 1.

Layer 3:

Convolution layer with 128 input channels, 256 output channels and kernel size 5 X 5 with padding 1.

Fully Connected Layer 1:

The Hidden Layer contains 1024 neurons, and output layer contains 1024.

Fully Connected Layer 2:

The Hidden Layer contains 1024 neurons, and output layer contains 512.

Fully Connected Layer 3:

The Hidden Layer contains 512 neurons, and output layer contains 4.

4. Training Process:

Throughout 80 epochs, a learning rate of 0.00001 was used to train the models. We have chosen Cross-entropy loss as the loss function, and Adam is an optimizer. To train the model, we tried a range of kernel sizes. Three and five different kernel sizes have been employed. The model performed best when a 3-layer convolution net was used with a 3x3 kernel.

Results:

Main model 3x3 Kernel:

Following 80 epochs, the model with the stated kernel size attained a training accuracy of around 84.36%, a testing accuracy of 65.71%, and a validation accuracy of 66.13%. When compared to the other kernel, it performed better.

| | | | | |
|----------------|------------------|------------------|---------------------|--------------------|
| Epoch [65/80], | Tr Loss: 0.5527, | Tr Acc: 78.6694, | Val Loss: 0.864637, | Val Acc: 65.495209 |
| Epoch [66/80], | Tr Loss: 0.5491, | Tr Acc: 77.1605, | Val Loss: 0.875890, | Val Acc: 64.217255 |
| Epoch [67/80], | Tr Loss: 0.5510, | Tr Acc: 76.5432, | Val Loss: 0.846920, | Val Acc: 66.453674 |
| Epoch [68/80], | Tr Loss: 0.5224, | Tr Acc: 78.3265, | Val Loss: 0.852822, | Val Acc: 65.495209 |
| Epoch [69/80], | Tr Loss: 0.5163, | Tr Acc: 78.3265, | Val Loss: 0.833690, | Val Acc: 65.175720 |
| Epoch [70/80], | Tr Loss: 0.4942, | Tr Acc: 80.1097, | Val Loss: 0.850402, | Val Acc: 63.897766 |
| Epoch [71/80], | Tr Loss: 0.5006, | Tr Acc: 80.1097, | Val Loss: 0.849136, | Val Acc: 66.773163 |
| Epoch [72/80], | Tr Loss: 0.4843, | Tr Acc: 80.6584, | Val Loss: 0.845640, | Val Acc: 64.217255 |
| Epoch [73/80], | Tr Loss: 0.4817, | Tr Acc: 81.3443, | Val Loss: 0.858645, | Val Acc: 65.814697 |
| Epoch [74/80], | Tr Loss: 0.4425, | Tr Acc: 82.5789, | Val Loss: 0.904472, | Val Acc: 63.897766 |
| Epoch [75/80], | Tr Loss: 0.4599, | Tr Acc: 80.8642, | Val Loss: 0.897322, | Val Acc: 66.134186 |
| Epoch [76/80], | Tr Loss: 0.4542, | Tr Acc: 81.3443, | Val Loss: 0.864969, | Val Acc: 66.773163 |
| Epoch [77/80], | Tr Loss: 0.4544, | Tr Acc: 82.1674, | Val Loss: 0.921109, | Val Acc: 65.495209 |
| Epoch [78/80], | Tr Loss: 0.4313, | Tr Acc: 82.7846, | Val Loss: 0.917887, | Val Acc: 67.412140 |
| Epoch [79/80], | Tr Loss: 0.4302, | Tr Acc: 83.3333, | Val Loss: 0.906059, | Val Acc: 64.856232 |
| Epoch [80/80], | Tr Loss: 0.4008, | Tr Acc: 84.3621, | Val Loss: 0.948464, | Val Acc: 66.134186 |

Variant 1:

The models change 3 layers convolution to 5 layers, under training for 100 epochs using a learning rate of 0.00001 and a kernel size of 3. We have chosen Cross-entropy loss as the loss function, while Adam is an optimizer. The model achieved a training accuracy of around 79.90% and a testing accuracy of 60.70% and a validation accuracy of 57.50 %.

```

Epoch [85/100], Tr Loss: 0.5528, Tr Acc: 76.2003, Val Loss: 1.114243, Val Acc: 61.022366
Epoch [86/100], Tr Loss: 0.5386, Tr Acc: 76.6804, Val Loss: 1.043532, Val Acc: 61.022366
Epoch [87/100], Tr Loss: 0.5337, Tr Acc: 77.0919, Val Loss: 0.975005, Val Acc: 61.980831
Epoch [88/100], Tr Loss: 0.5226, Tr Acc: 77.9150, Val Loss: 1.063114, Val Acc: 61.661339
Epoch [89/100], Tr Loss: 0.5470, Tr Acc: 76.2689, Val Loss: 0.993515, Val Acc: 58.466454
Epoch [90/100], Tr Loss: 0.5695, Tr Acc: 75.3772, Val Loss: 0.944017, Val Acc: 60.702873
Epoch [91/100], Tr Loss: 0.5241, Tr Acc: 76.6804, Val Loss: 1.156326, Val Acc: 61.022366
Epoch [92/100], Tr Loss: 0.5048, Tr Acc: 78.4636, Val Loss: 1.080122, Val Acc: 62.619804
Epoch [93/100], Tr Loss: 0.5649, Tr Acc: 75.9259, Val Loss: 1.030202, Val Acc: 59.424919
Epoch [94/100], Tr Loss: 0.5310, Tr Acc: 76.9547, Val Loss: 1.085662, Val Acc: 62.300320
Epoch [95/100], Tr Loss: 0.5142, Tr Acc: 77.2977, Val Loss: 1.031995, Val Acc: 61.022366
Epoch [96/100], Tr Loss: 0.4915, Tr Acc: 79.6982, Val Loss: 1.133656, Val Acc: 62.300320
Epoch [97/100], Tr Loss: 0.5278, Tr Acc: 77.7778, Val Loss: 1.025365, Val Acc: 62.300320
Epoch [98/100], Tr Loss: 0.4802, Tr Acc: 79.1495, Val Loss: 1.236598, Val Acc: 61.022366
Epoch [99/100], Tr Loss: 0.4588, Tr Acc: 81.0014, Val Loss: 1.204501, Val Acc: 62.619804
Epoch [100/100], Tr Loss: 0.4830, Tr Acc: 79.9040, Val Loss: 1.224823, Val Acc: 57.507984

```

Variant 2:

The models changed 3 kernel size to 5 kernel size, underwent training for 100 epochs using a learning rate of 0.00001 and a kernel size of 5. We have chosen Cross-entropy loss as the loss function, while Adam is an optimizer. The model achieved a training accuracy of around 88.75% and a testing accuracy of 63.89% and a validation accuracy of 61.98%.

```

Epoch [85/100], Tr Loss: 0.4673, Tr Acc: 79.7668, Val Loss: 1.122540, Val Acc: 60.383385
Epoch [86/100], Tr Loss: 0.4155, Tr Acc: 82.6475, Val Loss: 1.020994, Val Acc: 60.702873
Epoch [87/100], Tr Loss: 0.4157, Tr Acc: 82.7160, Val Loss: 1.114942, Val Acc: 61.980831
Epoch [88/100], Tr Loss: 0.3933, Tr Acc: 84.6365, Val Loss: 1.233695, Val Acc: 59.105431
Epoch [89/100], Tr Loss: 0.3860, Tr Acc: 84.7051, Val Loss: 1.120575, Val Acc: 61.341850
Epoch [90/100], Tr Loss: 0.3847, Tr Acc: 84.3621, Val Loss: 1.157611, Val Acc: 62.300320
Epoch [91/100], Tr Loss: 0.3878, Tr Acc: 84.5679, Val Loss: 1.154385, Val Acc: 61.980831
Epoch [92/100], Tr Loss: 0.3631, Tr Acc: 85.7339, Val Loss: 1.161813, Val Acc: 59.105431
Epoch [93/100], Tr Loss: 0.3734, Tr Acc: 85.0480, Val Loss: 1.164812, Val Acc: 61.980831
Epoch [94/100], Tr Loss: 0.3362, Tr Acc: 86.2826, Val Loss: 1.267612, Val Acc: 59.744408
Epoch [95/100], Tr Loss: 0.3447, Tr Acc: 86.4883, Val Loss: 1.271942, Val Acc: 61.980831
Epoch [96/100], Tr Loss: 0.3470, Tr Acc: 85.3909, Val Loss: 1.162644, Val Acc: 61.980831
Epoch [97/100], Tr Loss: 0.3175, Tr Acc: 87.6543, Val Loss: 1.315669, Val Acc: 60.702873
Epoch [98/100], Tr Loss: 0.3192, Tr Acc: 87.5857, Val Loss: 1.268382, Val Acc: 63.258785
Epoch [99/100], Tr Loss: 0.2929, Tr Acc: 88.4774, Val Loss: 1.270722, Val Acc: 61.022366
Epoch [100/100], Tr Loss: 0.2944, Tr Acc: 88.7517, Val Loss: 1.294727, Val Acc: 61.980831

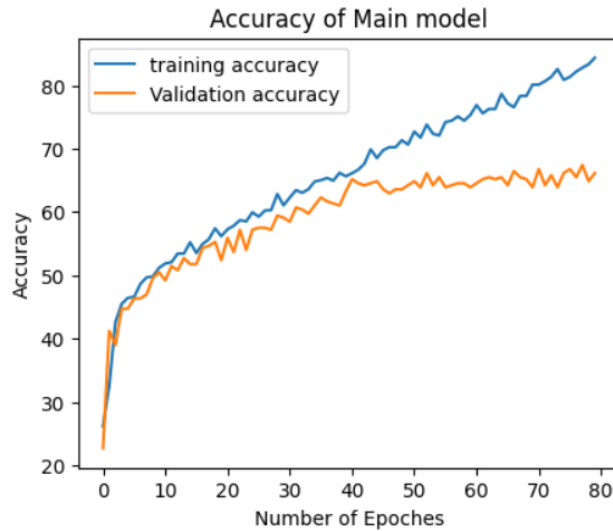
```

Chapter 6: Evaluation

Visualizing Model's Training and Validation Accuracy and Loss:

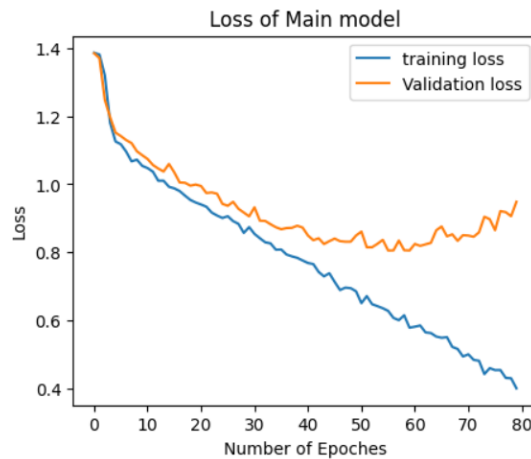
Main Model:

Visualizing Accuracy:



From the above graph we can say that when the number of epochs increases, the accuracy of main model also increases.

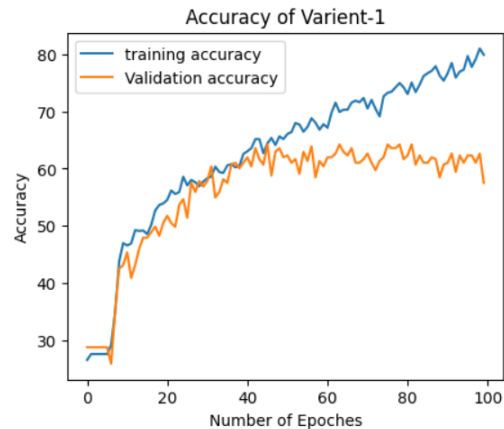
Visualizing Loss:



From the above graph we can say that when the number of epochs increases, the loss of the main model decreases.

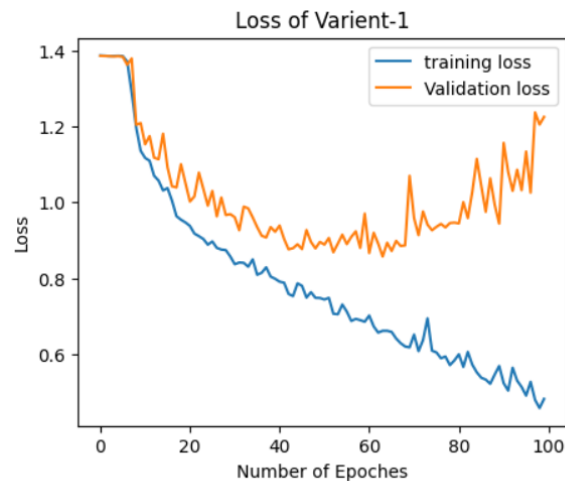
Variant 1:

Visualizing Accuracy:



From the above graph we can say that when number of epochs increases, the training accuracy of variant 1 model also increases but at the same time for the validation accuracy remains constant after 60%. So, this model performs overfitting.

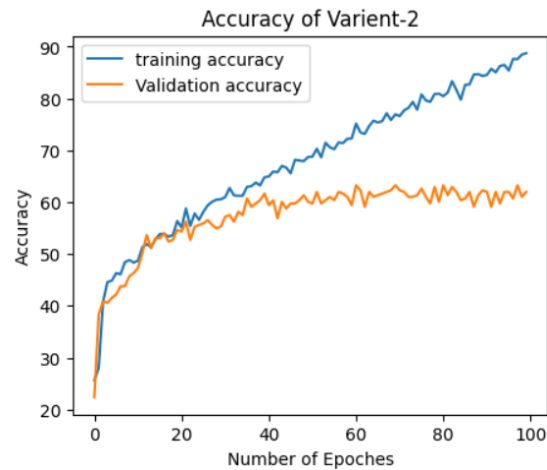
Visualizing Loss:



From the above graph we can say that when number of epochs increases, the training loss of variant 1 model decreases but at the same time for the validation loss after 60 epochs it starts increasing. So, this model performs overfitting.

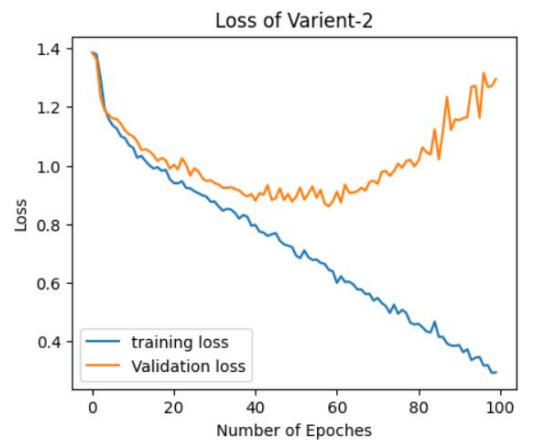
Variant 2:

Visualizing Accuracy:



From the above graph we can say that when number of epochs increases, the training accuracy of variant 2 model also increases but at the same time for the validation accuracy remains constant after 60%. So, this model performs overfitting.

Visualizing Loss:



From the above graph we can say that when number of epochs increases, the training loss of variant 2 model decreases but at the same time for the validation loss after 60 epochs it starts increasing. So, this model performs overfitting.

Performance Metrics:

Main Model:

Evaluation of Main model on Testing Data :

Precision_macro: 0.6695

precision_micro: 0.6581

Recall_macro: 0.6659

recall_micro: 0.6581

Accuracy: 0.6581

F1-Measure_macro: 0.6573

F1-Measure_micro: 0.6581

Variant 1:

Evaluation of Variant-1 on Testing Data :

Precision_macro: 0.6228

precision_micro: 0.6070

Recall_macro: 0.6173

recall_micro: 0.6070

Accuracy: 0.6070

F1-Measure_macro: 0.6182

F1-Measure_micro: 0.6070

Variant 2:

Evaluation of Variant-2 on Testing Data :

Precision_macro: 0.6448

precision_micro: 0.6390

Recall_macro: 0.6447

recall_micro: 0.6390

Accuracy: 0.6390

F1-Measure_macro: 0.6384

F1-Measure_micro: 0.6390

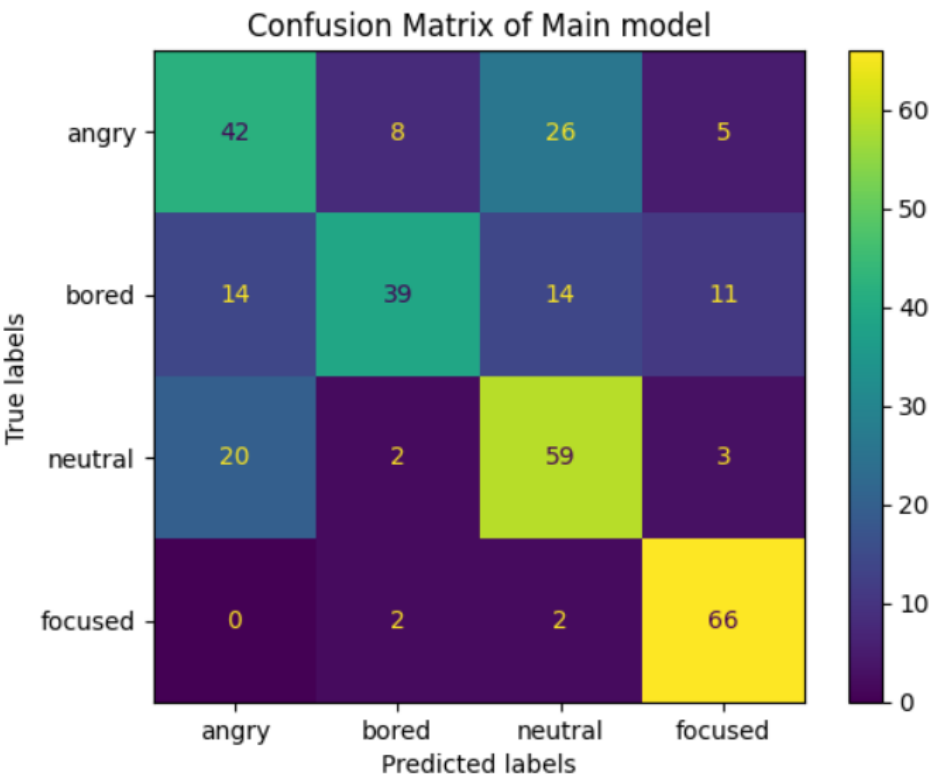
| Model | Macro | | | Micro | | | Accuracy |
|------------|--------|--------|--------|--------|--------|--------|----------|
| | P | R | F1 | P | R | F1 | |
| Main Model | 0.6695 | 0.6659 | 0.6573 | 0.6581 | 0.6581 | 0.6581 | 0.6581 |
| Variant1 | 0.6228 | 0.6173 | 0.6182 | 0.6070 | 0.6070 | 0.6070 | 0.6070 |
| Variant2 | 0.6448 | 0.6447 | 0.6384 | 0.6390 | 0.6390 | 0.6390 | 0.6390 |

The main model has a testing accuracy that is higher than Variant 1 and Variant 2.

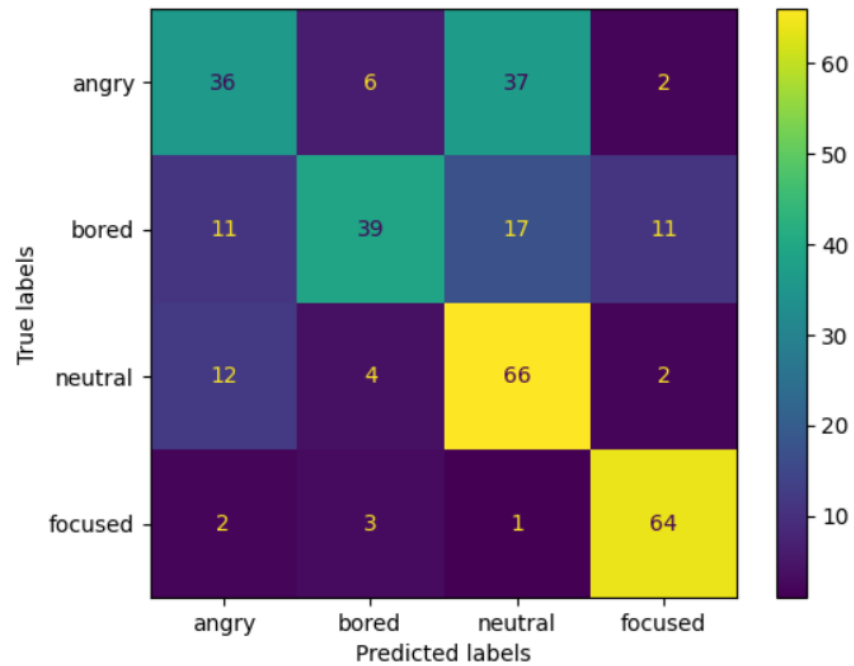
Confusion Matrix Analysis:

The prevalent misclassification in the confusion matrix occurs with the "boring" class, primarily stemming from subtle visual distinctions leading to an elevated number of false negatives. Conversely, the model demonstrates proficiency in accurately identifying neutral and focused facial expressions. These classes exhibit substantial visual disparities, providing distinct feature sets for the model to learn from. In contrast, the more nuanced features of angry and bored expressions contribute to a higher likelihood of misclassifications in these categories. This underscores the model's tendency to exhibit bias towards classes with less distinct visual characteristics.

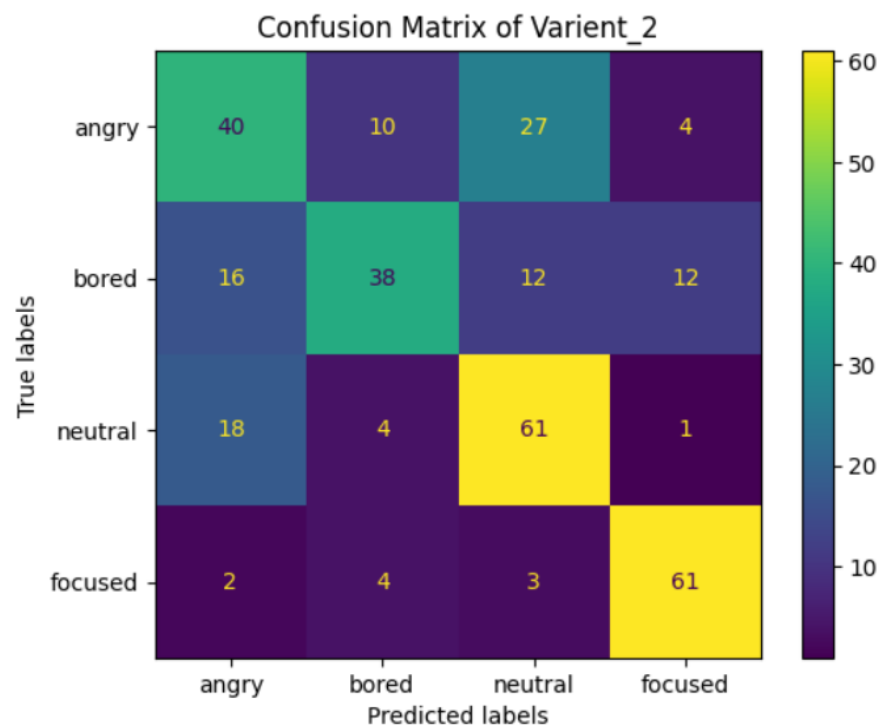
Main Model:



Variant 1:



Variant 2:



Impact of Architectural Variation:

We explored three distinct models, and Variant 1, featuring five convolution layers, encountered difficulties in capturing sufficient details for effective classification. The model grappled with overfitting issues, prompting us to mitigate the problem by reducing the depth of the network. This adjustment involved the removal of two convolution layers to enhance the model's ability to extract intricate features.

In our exploration of model training, we conducted experiments involving varying kernel sizes—specifically, 3 and 5. Notably, the model exhibited optimal performance when utilizing a 3x3 kernel. The detailed insights into these experiments are elaborated upon in the Training Process section above.

Chapter 7: Conclusion

The model with a 3x3 kernel and 3 convolution layers emerged as the most effective, achieving a harmonious balance between training and testing accuracy (84.36% and 65.81%, respectively). This balance indicates successful feature extraction without notable issues of overfitting or underfitting. Larger kernel sizes, such as 5x5, resulted in overfitting. The 3-layer architecture proved optimal for our dataset, with each configuration change significantly influencing performance.

To enhance accuracy in training and validation, consider implementing data augmentation techniques. This involves diversifying the training set by introducing variations like rotation, resizing, or flipping of images. Such approaches contribute to a more comprehensive training set, promoting better generalization by the model. Additionally, explore the utilization of pre-trained models, fine-tuning them on your specific dataset. This technique leverages learned features from extensive and diverse datasets, potentially improving the model's performance on your facial image analysis task.

References

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<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>