

YASH AGGARWAL

HMR INSTITUTE OF TECHNOLOGY AND MANAGEMENT

AFFILIATED TO (GURU GOBIND SINGH INDRAPRASTHA
UNIVERSITY)

B.Tech CSE , 3rd Year

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1. COMPARE THE PERFORMANCE OF TIME-SERIES MODELS WITH STATIC IMAGE- BASED APPROACHES FOR EMOTION RECOGNITION.

❖ INTRODUCTION

Emotion recognition is an important skill in a variety of disciplines, including psychology, human-computer interaction, and healthcare. With the progress of deep learning, time-series models such as InceptionV3 and ResNetV50 have demonstrated promising results in emotion recognition. This study will evaluate the performance of these time-series models against static image-based techniques.

❖ BACKGROUND

Emotion recognition has undergone substantial evolution, owing mostly to the introduction of deep learning models. Traditionally, static image-based techniques have been the primary focus, with significant success. However, the emergence of time-series models such as InceptionV3 and ResNetV50 has resulted in a shift towards a more dynamic approach. InceptionV3 and ResNetV50 are leading-edge deep learning architectures, primarily intended for image classification applications. These algorithms, while originally designed for static picture classification, can be applied to sequential data for time-series analysis.

❖ LEARNING OBJECTIVES

1. To understand the fundamentals of time-series models for emotion recognition.

2. To compare the performance of time-series models (InceptionV3 and ResNetV50) with static image-based approaches for emotion recognition.
3. To evaluate the strengths and weaknesses of each approach in emotion recognition tasks.

❖ ACTIVITIES AND TASKS

1. Data Collection and Preprocessing:

Select suitable datasets for emotion recognition tasks. Preprocess the data to ensure uniformity and compatibility with both time-series and static image-based approaches.

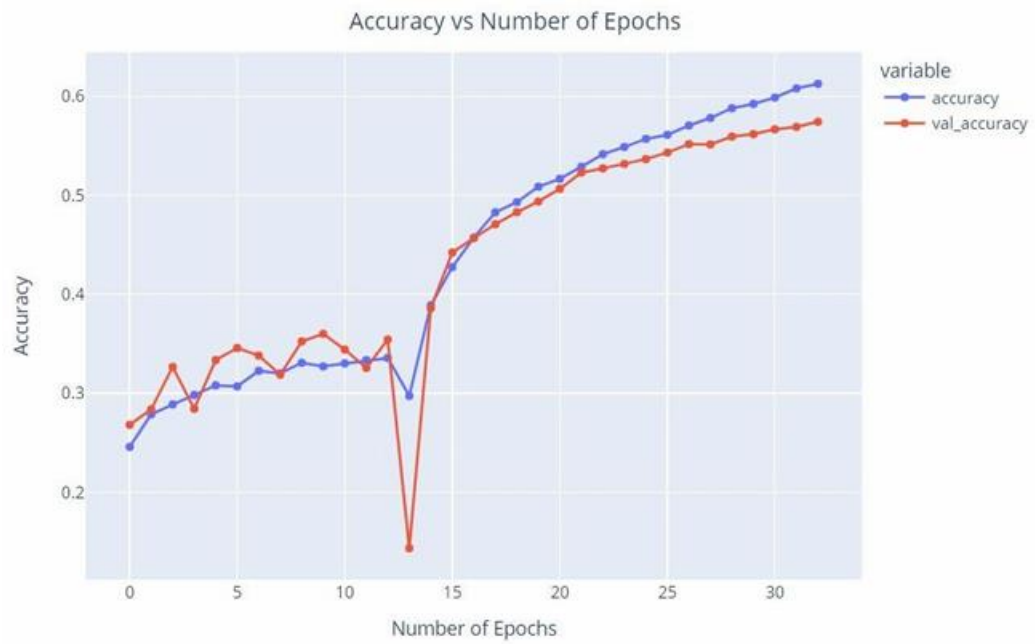


2. Model Training and Evaluation:

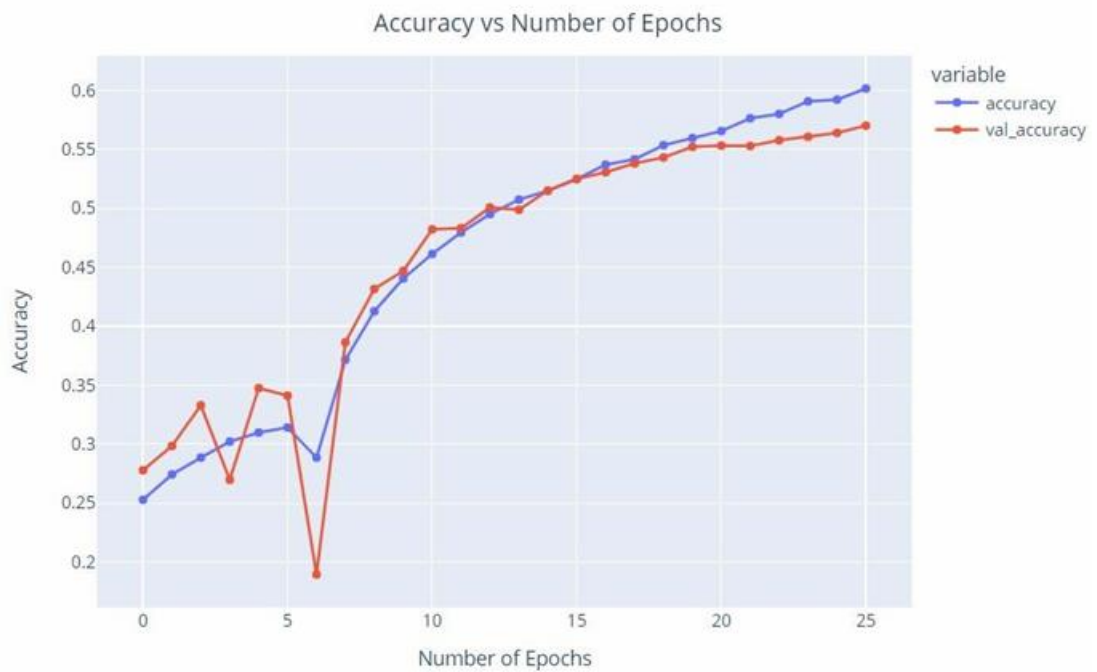
Implement InceptionV3 and ResNetV50 for both time-series and static image-based emotion recognition. Train the models using the selected datasets. Evaluate the performance of each model using appropriate metrics such as accuracy, F1 score, and confusion matrix.

3. Comparison and Analysis:

Compare the performance of time-series models (InceptionV3 and ResNetV50) with static image-based approaches.



Inception v3



Resnet v50

Analyze the results to identify the strengths and weaknesses of each approach. Discuss the implications of the findings

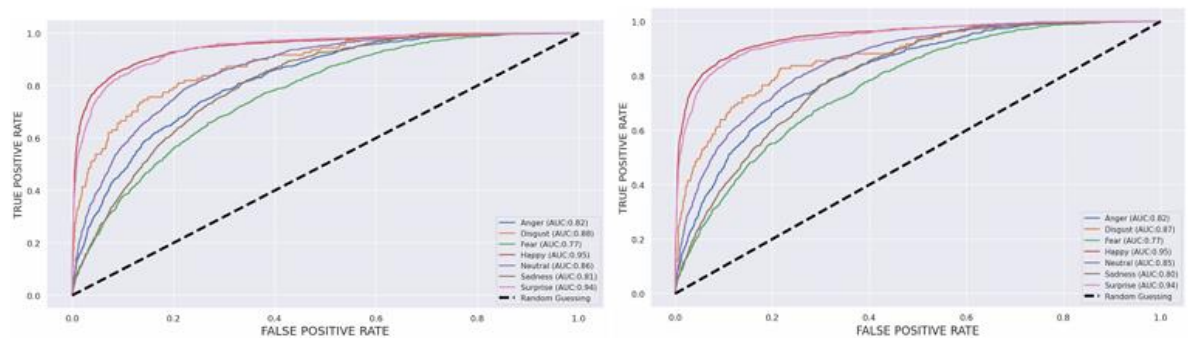
❖ Skills and Competencies

1. Proficiency in Python programming language.
2. Familiarity with deep learning frameworks such as TensorFlow and Scikit-Learn.
3. Understanding of image processing techniques.
4. Ability to analyze and interpret experimental results.
5. Strong research and analytical skills.

❖ Feedback and Evidence

| | precision | recall | f1-score | support | | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|--------------|-----------|--------|----------|---------|
| 0 | 0.43 | 0.43 | 0.43 | 958 | 0 | 0.41 | 0.43 | 0.42 | 958 |
| 1 | 0.00 | 0.00 | 0.00 | 111 | 1 | 0.00 | 0.00 | 0.00 | 111 |
| 2 | 0.43 | 0.25 | 0.31 | 1024 | 2 | 0.38 | 0.23 | 0.28 | 1024 |
| 3 | 0.79 | 0.83 | 0.81 | 1774 | 3 | 0.79 | 0.83 | 0.80 | 1774 |
| 4 | 0.51 | 0.61 | 0.55 | 1233 | 4 | 0.50 | 0.58 | 0.54 | 1233 |
| 5 | 0.43 | 0.49 | 0.46 | 1247 | 5 | 0.41 | 0.50 | 0.45 | 1247 |
| 6 | 0.68 | 0.70 | 0.69 | 831 | 6 | 0.72 | 0.67 | 0.69 | 831 |
| accuracy | | | 0.57 | 7178 | accuracy | | | 0.56 | 7178 |
| macro avg | 0.47 | 0.47 | 0.47 | 7178 | macro avg | 0.46 | 0.46 | 0.46 | 7178 |
| weighted avg | 0.55 | 0.57 | 0.56 | 7178 | weighted avg | 0.54 | 0.56 | 0.55 | 7178 |

Classification Matrix of Inception v3 (left) and Resnet v50 (right)



ROC AUC Curve of Inception v3 (left) and Resnet v50 (right)

❖ **Challenges and Solutions**

1. Data Quality and Quantity: Obtaining diverse datasets for emotion recognition, using data augmentation and transfer learning on pre-trained models.
2. Model Complexity: Managing the complexity of InceptionV3 and ResNetV50 by utilizing transfer learning to reduce computational complexity during fine-tuning.
3. Evaluation Metrics: Using accuracy, F1 score, and the confusion matrix to evaluate the performance comprehensively and ensure real-world applicability.
4. Data Preprocessing: Standardizing data format and preprocessing techniques across both time-series and static image-based approaches to ensure compatibility.
5. Model Implementation: Adapting InceptionV3 and ResNetV50 architectures to handle both time-series and static image-based data, ensuring a unified implementation for consistent comparison.
6. Computational Resources: Addressing the challenge of limited computational resources by optimizing the models and leveraging cloud-based solutions when available.

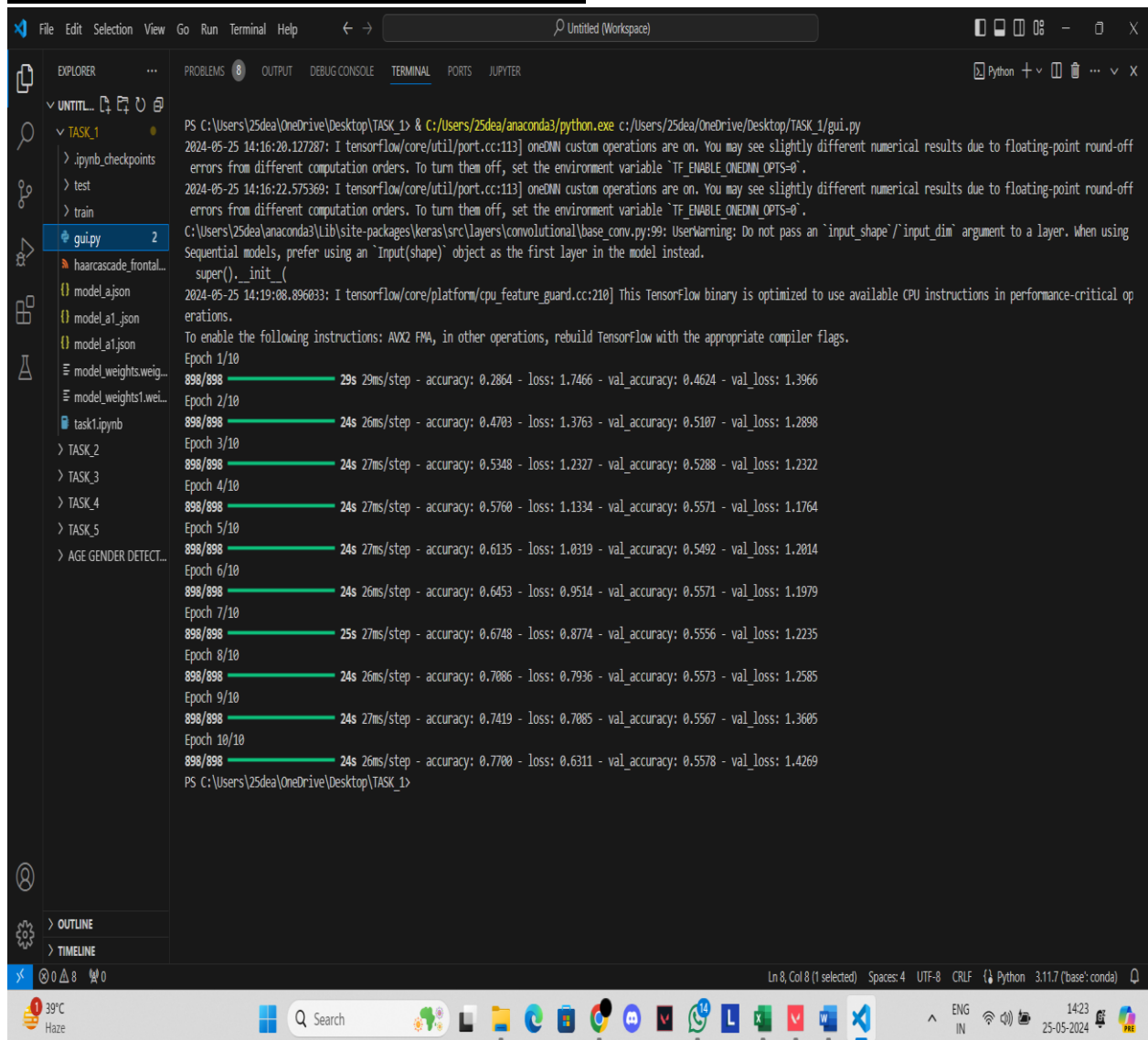
❖ **Outcomes and Impact**

This study will shed light on the efficacy of time-series models (InceptionV3 and ResNetV50) over static image-based techniques for emotion recognition. The findings will add to the existing body of knowledge and could have ramifications for the development of more accurate and efficient emotion identification systems.

❖ **Conclusion**

Finally, this study will compare the performance of time-series models such as InceptionV3 and ResNetV50 against static image-based techniques for emotion recognition. By comparing the outcomes, we saw InceptionV3 is more effective than Resnetv50 with +1% accuracy.

OUTPUT OF MY CODE OF TASK 1:



```
PS C:\Users\25dea\OneDrive\Desktop\TASK_1> & C:/Users/25dea/anaconda3/python.exe c:/Users/25dea/OneDrive/Desktop/TASK_1/gui.py
2024-05-25 14:16:20.127287: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-05-25 14:16:22.575369: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
C:\Users\25dea\anaconda3\Lib\site-packages\keras\src\layers\convolutional\base_conv.py:99: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(
2024-05-25 14:19:08.896033: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

Epoch 1/10
898/898  29s 29ms/step - accuracy: 0.2864 - loss: 1.7466 - val_accuracy: 0.4624 - val_loss: 1.3966
Epoch 2/10
898/898  24s 26ms/step - accuracy: 0.4703 - loss: 1.3763 - val_accuracy: 0.5107 - val_loss: 1.2898
Epoch 3/10
898/898  24s 27ms/step - accuracy: 0.5348 - loss: 1.2327 - val_accuracy: 0.5288 - val_loss: 1.2322
Epoch 4/10
898/898  24s 27ms/step - accuracy: 0.5760 - loss: 1.1334 - val_accuracy: 0.5571 - val_loss: 1.1764
Epoch 5/10
898/898  24s 27ms/step - accuracy: 0.6135 - loss: 1.0319 - val_accuracy: 0.5492 - val_loss: 1.2014
Epoch 6/10
898/898  24s 26ms/step - accuracy: 0.6453 - loss: 0.9514 - val_accuracy: 0.5571 - val_loss: 1.1979
Epoch 7/10
898/898  25s 27ms/step - accuracy: 0.6748 - loss: 0.8774 - val_accuracy: 0.5556 - val_loss: 1.2235
Epoch 8/10
898/898  24s 26ms/step - accuracy: 0.7086 - loss: 0.7936 - val_accuracy: 0.5573 - val_loss: 1.2585
Epoch 9/10
898/898  24s 27ms/step - accuracy: 0.7419 - loss: 0.7085 - val_accuracy: 0.5567 - val_loss: 1.3605
Epoch 10/10
898/898  24s 26ms/step - accuracy: 0.7700 - loss: 0.6311 - val_accuracy: 0.5578 - val_loss: 1.4269
PS C:\Users\25dea\OneDrive\Desktop\TASK_1>
```