R & D Project Evaluation I

Academic Year- 2023-24

Project ID 28

Human emotion detection from face images

Submitted by

1. Rohan Bali BT21GCS059 CSE, Data Science
2. Shweta Singh BT21GCS162 CSE, Artificial Intelligence
3. Tanu BT21GCS006 CSE, Big Data Engineering

Supervisor - Dr. Santanu Roy

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CERTIFICATE BY SUPERVISOR(S)

This is to certify that the present R&D project entitled Human emotion detection from face images being submitted to NIIT University, Neemrana, in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology, in the area of BT/CSE/ECE/GIS, embodies faithful record of original research carried out by Rohan Bali, Shweta Singh and Tanu. She / He / They has / have worked under my/our guidance and supervision and that this work has not been submitted, in part or full, for any other degree or diploma of NIIT or any other University.

Place: NIIT University, Neemrana

Name of the Supervisor(s) with signature: Dr. Santanu Roy

Date: 22/05/24

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DECLARATION BY STUDENT(S)

I/We hereby declare that the project report entitled Human emotion detection from face images which is being submitted for the partial fulfilment of the Degree of Bachelor of Technology, at NIIT University, Neemrana, is an authentic record of my/our original work under the guidance of Dr. Santanu Roy. Due acknowledgements have been given in the project report to all other related work used. This has previously not formed the basis for the award of any degree, diploma, associate/fellowship or any other similar title or recognition in NIIT University or elsewhere.

Place: NIIT University, Neemrana

Date: 22/05/24

Rohan Bali	BT21GCS059	Data Science
Shweta Singh	BT21GCS162	Artificial Intelligence
Tanu	BT21GCS006	Big Data Engineering

Contents

1. Abstract

Human emotion detection from face images is a critical area of study with a plethora of real-world applications in human-computer interaction, security, and psychological research to name a few. Detecting human emotions from face images with high accuracy remains a challenge due to the heterogeneous nature of human faces. With distinct features ranging from face shape (difference in bone structure) and length (distance between facial features) to vivid details such as characteristics of the eyebrows, eyes, nose, lips, cheekbones, jawline and some uncommon features like birthmarks and scars. Facial muscles move these features into different positions, for example, wrinkling of the eyes and the eyebrows or stretching of the lips, creating facial expressions. In this work we evaluate the accuracy achieved by different deep learning models in this context. Deep learning models, specifically Convolutional Neural Networks are the most promising in detecting facial emotions due to their automatic feature extraction. We have trained several pre-trained models (initially trained on the ImageNet dataset) utilizing Convolutional Neural Networks (CNNs) on a human emotions dataset sourced from Kaggle.

2. Keywords

Human Emotion Detection, Facial Expression Recognition, Convolutional Neural Networks (CNNs), Pre-trained Models, ImageNet, Data Augmentation, FER2013 Dataset, IIITM Face Emotion Dataset, Facial Feature Extraction, Transfer Learning, Model Fine-tuning, Training Procedure, Evaluation Metrics, VGG-16 Architecture, Layer Freezing, Dropout, Global Average Pooling, Batch Normalization, Early Stopping.

3. Introduction

In analyzing human facial expressions, traditional methods often struggle to maintain accuracy and efficiency, especially in real-world, uncontrolled settings. Factors like varying poses and lighting conditions make it challenging to reliably identify emotions. Furthermore, human faces exhibit considerable diversity, even when expressing the same emotion, further complicating the task.
To address these challenges, our research focuses on developing an innovative system for automatic facial expression recognition. Central to our approach is the use of pre-trained Convolutional Neural Network (CNN) models. CNNs excel at extracting meaningful features from images, making them well-suited for this task. By incorporating novel methodologies in loss functions and

preprocessing techniques, we aim to enhance the accuracy and real-time applicability of facial expression recognition systems. Our study utilizes data augmentation techniques, such as scaling, rotation, and changes in brightness of the image, to increase the diversity and robustness of our training data. Additionally, we meticulously fine-tune hyperparameters and explore various optimization algorithms and learning rate schedulers to optimize model performance. As discussed above, in the field of facial emotion recognition, CNNs have shown great potential while maintaining efficiency in the models. Models previously trained on large-scale datasets like ImageNet are the foundation of this research work.

4. Related Work

[1] This paper states the importance of human emotion detection in human-computer interactions. The problem is considered solved for images taken in controlled environments. But in naturalistic conditions, where the poses and lighting on the face are not ideal, identifying emotions is complex. There is also a lot of heterogeneity in the faces of humans, even when showing the same emotions. The chosen dataset is FER2013, which consists of grayscale images of dimensions 48x48 pixels. These images are labeled into seven different categories. This dataset has images that replicate to some extent the difficult naturalistic conditions. The model used for identifying emotions is CNN (Convolutional Neural Network). This is a very popular model due to its efficiency in extracting features from images. Data augmentation is performed in the form of scaling, rotation, horizontal and vertical shifting, random cropping, etc. The experiments are run for many epochs, adjusting all the hyperparameters. The main model used is a VGGNet architecture, which is a CNN based model. Many optimizers as well as Learning Rate Schedulers are used too. The model is fine tuned in the end and a state-of-the-art accuracy of 73.28% is achieved.

[2] This study focuses on understanding emotions by analyzing signals from various sources. It aims to interpret these signals by utilizing an emotion recognition system. One main aspect involves detecting facial expressions automatically using neural classifier techniques, which have shown promising results in facial recognition. To describe differences in facial appearance visually, a novel feature descriptor named HOG-30 is introduced. The process begins with face recognition and preprocessing applied to original images. Computers are used to locate and identify facial regions, which are then cropped to desired sizes. After extracting expression features from preprocessed facial images, dimensionality reduction techniques are employed to manage high-dimensional data. Techniques for distinguishing between different facial expression features are selected, including face normalization to convergence fast and prevention of overfitting, affine

transformation to correct distortion from non-ideal camera angles, and face alignment to standardize poses before feature extraction.

[3] The paper investigates emotion detection and highlights critical elements for emotion classification using two facial expression datasets. Lighting variations are addressed by mean forms and dataset mapping. The model incorporates a Convolutional Neural Network (CNN) with Rectified Linear Units that consists of numerous convolutional layers and fully linked layers. A Recurrent Neural Network (RNN) transforms input order into sequential outputs in order to classify images by combining CNN-extracted properties. Gradient clipping and batch size settings of 32 are implemented. In regression, a CNN model with several hidden units and fully linked layers is trained over valence labels using mean squared error. Gradient descent with batch size, weight decay, and learning rate technique are applied. The combined CNN and RNN approach significantly improves face emotion identification, showcasing technological advances in this area.

5. Proposed Methodology

5.1 Dataset Acquisition and Preparation

5.1.1 Dataset Selection

For our model we have chosen two popular datasets in the human emotion recognition domain: FER2013 and Human Emotions Dataset. FER2013 is a very popular dataset launched back in 2013 and consists of 35,887 grayscale images of size 48 x 48 pixels. The dataset contains labeled images divided into seven classes: angry, disgust, fear, happy, sad, surprise, and neutral. FER2013 -" https://www.kaggle.com/datasets/msambare/fer2013"

The Human Emotions Dataset is comparatively new and consists of 9077 images. They are divided into three classes: Angry, Happy and Sad. The test set contains 2278 images with the class Happy containing the most images followed by Sad and Angry, and the train set contains 6799 images with Happy containing the most images followed by Sad and Angry. The dataset additionally encompasses significant attributes such as gender, the presence of mustaches, beards, eyeglasses, and the density of their hair. The images are grayscale. IIITM Face Emotion - "https://www.kaggle.com/datasets/muhammadhananasghar/human-emotions-datasethes/data"

5.1.2 Data Augmentation (Preprocessing)

Data preprocessing or data augmentation will be done on the images before running the model to increase the variety of data present in the dataset,to manage overfitting problem, and to reduce class imbalance problem by oversampling, thereby increasing robustness of the model. This allows the model to train on a more generalized dataset. Data augmentation will include methods like rotating the images (by 30 degrees), resizing (zooming in and out of certain areas), changing the brightness (from 0.7-1.3 of the original image), etc.

5.2 Pre-Trained Convolutional Neural Network

The model contains a pre-trained architecture that uses the concept of CNN's to extract features and classify them into the desired classes. A typical CNN consists of an input layer, numerous hidden layers and dense/fully connected layers. Each layer in the architechture is made of neurons. Neurons at each layer are connected to the neurons of the next layer through weights. Weights are responsible for transmission of information from one layer to another. Features are captured at various levels with the movement of data, which enhance its capability to recognize patterns and make predictions. The pre-trained architecture contains weights taken from the model trained on the ImageNet dataset. Transfer learning from such pre-trained models empowers the model to inherit knowledge about generic features and patterns present in natural images, thereby expediting the training process and enhancing performance in the specific task of emotion recognition.

The input layer takes raw image or preprocessed image data to enter the network. The convolutional layers are responsible for automatic relevant feature extraction. They have filter coefficients which are learnable filters which scan the image, detect patterns and features(i.e. edges, textures and shapes) by applying convolution operation on the image with filter weights . In addition we have activation functions like Rectified Linear Units(ReLu), which help in understanding complex relationships within the data.

In between, there are max-pooling layers. They facilitate downsampling of feature maps, reducing spatial dimensions, controlling complexity, and mitigating overfitting risks.

After the convolutional and max-pooling layers, we have densely connected layers, also called fully connected layers. These layers combine the important information from earlier layers and use it to figure out which emotions are in the images. Each connection between neurons in these layers has a weight, which determines how important it is for making predictions.

In the output layer, the neural network assigns probabilities to each class based on extracted features, with the final prediction made by selecting the class with the highest probability score. It serves as the final stage for classification tasks, such as emotion recognition from images.

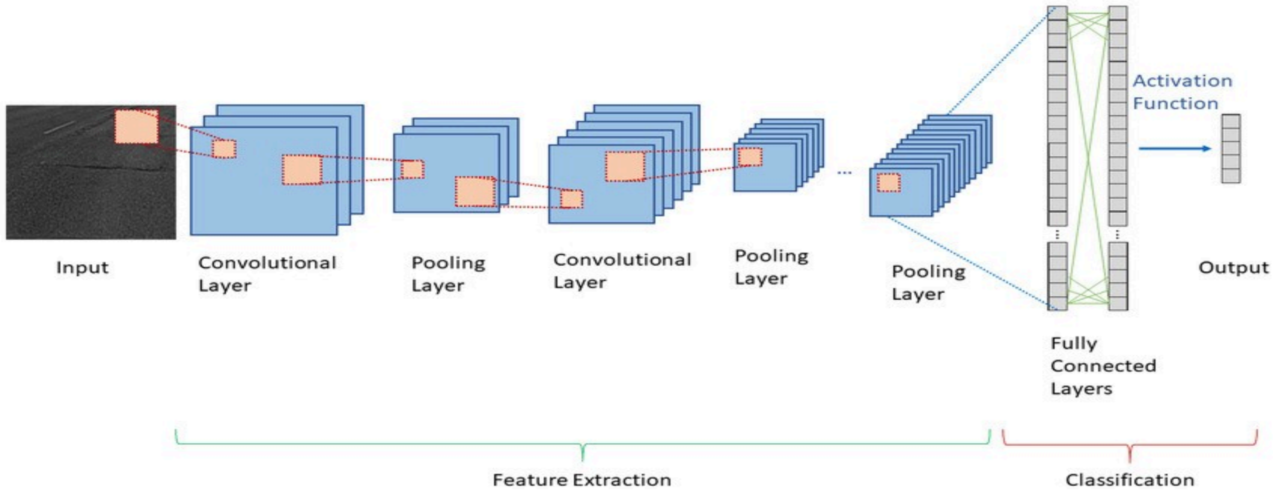


Fig 1: Convolutional Neural Network layers

5.3 Training Procedure

During training, we divided the dataset into training and testing sets to ensure accurate evaluation of our model's performance. Training set is further divided into training and validation sets. Iteratively, we fed batches of preprocessed images into the CNN model, adjusting its parameters through backpropagation to minimize loss. To prevent overfitting and optimize convergence, we applied techniques such as dropout and adaptive learning rate adjustment. Throughout the training process, we closely monitored performance metrics like accuracy. Training continued for multiple epochs until convergence was achieved. Finally, we evaluated the trained model on the test set to assess its performance on unseen data.

5.4 Evaluation Metrics

The pre-trained CNN model will be evaluated on the standard metrics like accuracy, precision, loss, and area under the curve (AUC) score. A confusion matrix will also tell us the number of true positives, true negatives, false positives and false negatives. These evaluation parameters provide the information about improvements that can be made.

6. Technology used / Methods

6.1 VGG-16

VGG-16 is a deep neural network architecture with 16 layers, mainly consisting of convolutional layers with small 3x3 filters, followed by max-pooling layers. It's known for its simplicity and effectiveness in image recognition tasks, achieving high accuracy by repeatedly stacking convolutional layers to capture complex patterns in images.

Table 1: Experiments on VGG-16 pretrained model

S.NO.	Changes	Loss	Accuracy	Precision	Recall	F1-Score
1	with lrd , Batch Normalization - 4 , Dense(32,32,32,7)	1.6618	0.5368	0.575	0.4939	0.4571
2	without lrd , Batch Normalization - 4 , Dense(32,32,32,7), with DropOut	2.4255	0.5628	0.5755	0.5543	0.5476
3	Batch Normalization - 2 , Dense (64,7), With Dropout	2.5664	0.5699	0.5793	0.5626	0.5543
4	Batch Normalization - 2 , Dense (128,7) , Remove Dropout	3.0993	0.5603	0.5662	0.5543	0.5525
5	Batch Normalization - 2 , Dense (128,7) , Remove Dropout , GAP	3.0876	0.5468	0.5535	0.5385	0.5429
6	Batch Normalization - 2 , Dense (128,7) , Remove Dropout , GAP, early stopping(patience-10)	2.0141	0.5528	0.5718	0.5295	0.5365
7	Batch Normalization - 2 , Dense (64,7) , Remove Dropout , GAP, early stopping(patience-10)	1.778	0.5627	0.5957	0.5348	0.5411
8	Batch Normalization - 2 , Dense (64,7) , Remove Dropout , GAP, early stopping(patience-10),kernel_initializer =glorot_uniform	1.9389	0.5581	0.5862	0.5327	0.5299
9	Batch Normalization - 2 , Dense (64,7) , Remove Dropout , GAP, early stopping(patience-20)	2.8437	0.5637	0.5713	0.556	0.5426

6.2 MobileNet V2

MobileNet V2, introduced by Mark Sandler, is a lightweight and computationally efficient model for object detection. It is said to perform well on mobile devices, thus the name MobileNet. It is a better model than its predecessor, MobileNet V1, Improving the performance while remaining compact and efficient.

Table 2: Experiments on MobileNet V2 pretrained model

S.NO.	Changes	Loss	Accuracy	Precision	Recall	F1 score
1	with lrd, batch normalization	0.9724	0.6252	0.6307	0.6252	0.6201
2	with lrd, batch normalization - 4, Dense(32, 32, 32, 7)	2.5013	0.5933	0.599	0.5897	0.5548
3	with lrd, batch normalization - 4, Dense(32, 32, 32, 7), Input resized to 192x192	2.1281	0.6206	0.6283	0.6156	0.5897
4	without lrd, batch normalization - 4, Dense(32, 32, 7), Input resized to 192x192, 50% freeze	2.6474	0.5513	0.5595	0.5447	0.4656
5	without lrd, batch normalization - 3, Dense(64, 32, 7), Input resized to 192x192	5.2727	0.1995	0.1726	0.747	0.0921

6.3 ResNet-50

ResNet-50 is an advanced neural network crafted by researchers at Microsoft Research. Noteworthy for its 50 layers of convolutional and pooling operations, it stands out for its depth. The innovation lies in its "residual connections," which tackle issues encountered in very deep neural networks. These connections enable smoother information flow through layers, overcoming the problem of vanishing gradients and maintaining performance quality. ResNet-50 excels in tasks like image classification, object detection, and segmentation in computer vision.

Table 3: Experiments on ResNet-50 pretrained model

S No.	Changes	Loss	Accuracy	Precision	Recall	F1-Score
1	100% Freezing Flatten Layer	1.5176	0.4585	0.6166	0.3130	0.4152
2	50% Freezing Flatten Layer	1.9174	0.5706	0.5798	0.5568	0.5681
3	0% Freezing Flatten Layer	1.7067	0.5313	0.5547	0.5070	0.5297
4	0% Freezing GAP Layer	1.7847	0.5047	0.5384	0.4823	0.5088
5	50% Freezing GAP Layer	1.8993	0.5716	0.5840	0.5591	0.5713
6	100% Freezing GAP Layer	1.5300	0.4146	0.7040	0.1286	0.2174
7	Removed Dropout, GAP	1.9575	0.4237	0.4784	0.3615	0.4118
8	Removed Dropout, flatten (Flatten) (None, 8192)	2.8626	0.4585	0.4727	0.4398	0.4557

6.4 Xception

Xception is a deep learning model introduced in 2017, and uses depthwise separable convolutions. This architecture replaces traditional convolutional layers with two separate operations, significantly reducing parameters and computational complexity while maintaining or improving performance. With pre-trained models available, Xception has demonstrated extremely accurate performance on human emotion detection.

7. Results and Analysis

The research delves into the application of pretrained models, investigating a range of methodologies to improve model efficacy. We explore techniques such as layer freezing, dropout implementation, and Global Average Pooling. Furthermore, we vary the number of batch normalization layers, dense layers, and convolutional layers, while also employing early stopping with differing patience values to optimize model training and enhance accuracy.

Table 4 - Fer 2013 Dataset

S.No.	Model	Loss	Accuracy	Precision	Recall	F1- Score
1.	VGG-16	1.6618	0.5368	0.575	0.4939	0.4571
2.	MobileNet V2	0.9724	0.6252	0.6307	0.6252	0.6201
3.	Resnet 50	1.9174	0.5706	0.5798	0.5568	0.5777

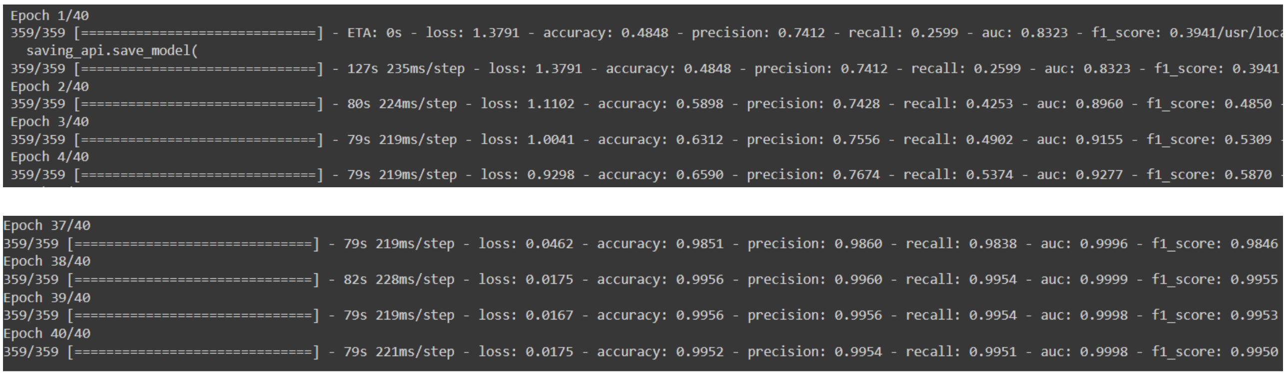
Table 5- Human Emotion dataset

S.No.	Model	Loss	Accuracy	Precision	Recall	F1-Score
1.	MobileNet-V2	1.5631	0.7533	0.755	0.752	0.7414
2.	Resnet 50	0.4312	0.8247	0.8672	0.7814	0.8247
3.	Xception	0.3638	0.8718	0.8650	0.8563	0.8601

Table 6 - MobileNet V2 on Human Emotion Dataset

S.No.	Changes	Loss	Accuracy	Precision	Recall	F1-Score
1.	50% freezing and 50% fine tuning, GAP	0.5953	0.9093	0.9103	0.9082	0.9008
2.	100% fine tuning,GAP	1.5631	0.7533	0.755	0.752	0.7414
3.	75% freeze ,GAP	2.3372	0.7744	0.7746	0.774	0.7617

FER 2013 -



```
Epoch 1/40
359/359 [============================] - ETA: 0s - loss: 1.3791 - accuracy: 0.4848 - precision: 0.7412 - recall: 0.2599 - auc: 0.8323 - f1_score: 0.3941/usr/loc
  saving_api.save_model(
359/359 [============================] - 127s 235ms/step - loss: 1.3791 - accuracy: 0.4848 - precision: 0.7412 - recall: 0.2599 - auc: 0.8323 - f1_score: 0.3941
Epoch 2/40
359/359 [============================] - 80s 224ms/step - loss: 1.1102 - accuracy: 0.5898 - precision: 0.7428 - recall: 0.4253 - auc: 0.8960 - f1_score: 0.4850
Epoch 3/40
359/359 [============================] - 79s 219ms/step - loss: 1.0041 - accuracy: 0.6312 - precision: 0.7556 - recall: 0.4902 - auc: 0.9155 - f1_score: 0.5309
Epoch 4/40
359/359 [============================] - 79s 219ms/step - loss: 0.9298 - accuracy: 0.6590 - precision: 0.7674 - recall: 0.5374 - auc: 0.9277 - f1_score: 0.5870
```

```
Epoch 37/40
359/359 [============================] - 79s 219ms/step - loss: 0.0462 - accuracy: 0.9851 - precision: 0.9860 - recall: 0.9838 - auc: 0.9996 - f1_score: 0.9846
Epoch 38/40
359/359 [============================] - 82s 228ms/step - loss: 0.0175 - accuracy: 0.9956 - precision: 0.9960 - recall: 0.9954 - auc: 0.9999 - f1_score: 0.9955
Epoch 39/40
359/359 [============================] - 79s 219ms/step - loss: 0.0167 - accuracy: 0.9956 - precision: 0.9956 - recall: 0.9954 - auc: 0.9998 - f1_score: 0.9953
Epoch 40/40
359/359 [============================] - 79s 221ms/step - loss: 0.0175 - accuracy: 0.9952 - precision: 0.9954 - recall: 0.9951 - auc: 0.9998 - f1_score: 0.9950
```

Fig 2: Model.fit()

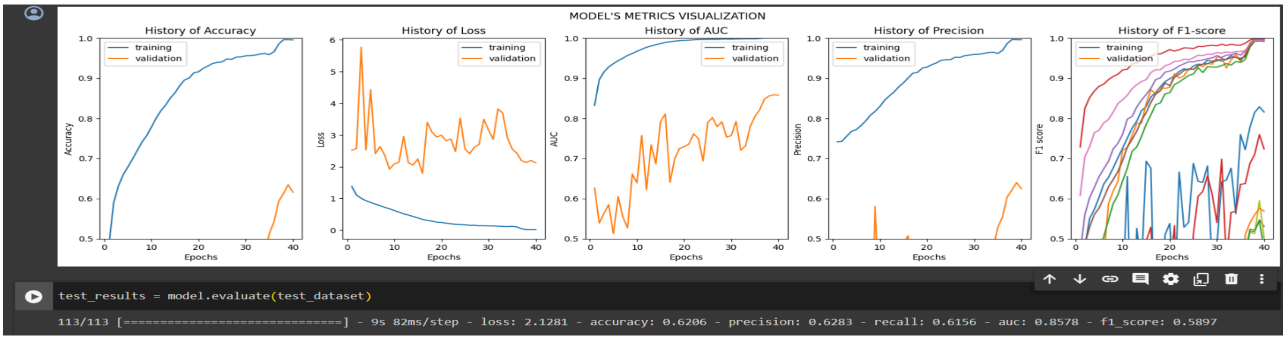


Fig 3: Model's Evaluation Metrics Visualization

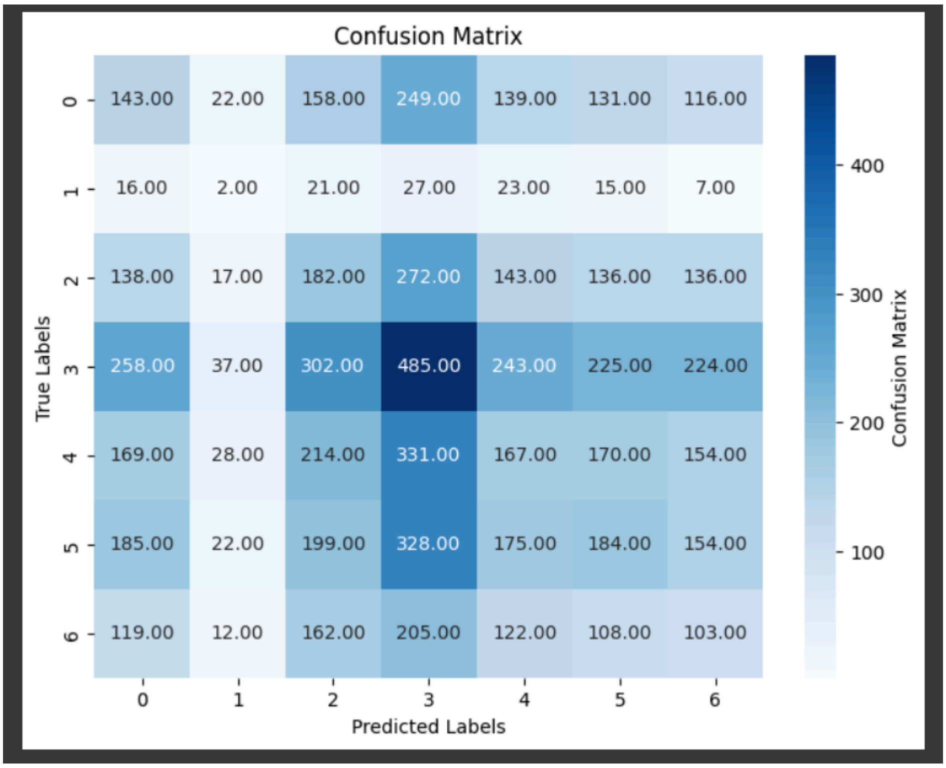


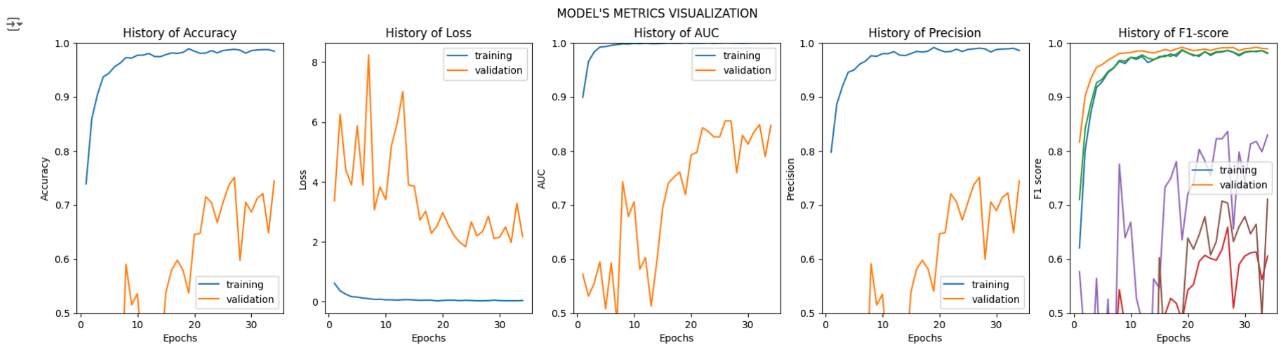
Fig 4: Model's Confusion Matrix

Human Emotion Dataset -

```
history=model.fit(train_dataset,validation_data=valid_dataset,epochs = 40,verbose = 1,callbacks=[mcp,es])

Epoch 1/40
218/218 [==============================] - ETA: 0s - loss: 0.6162 - accuracy: 0.7390 - precision: 0.7976 - recall: 0.6672 - auc: 0.8990 - f1_score: 0.7156/usr/local/lib/python3.10/dist-packages/keras/src
  saving_api.save_model(
218/218 [==============================] - 43s 139ms/step - loss: 0.6162 - accuracy: 0.7390 - precision: 0.7976 - recall: 0.6672 - auc: 0.8990 - f1_score: 0.7156 - val_loss: 3.3710 - val_accuracy: 0.4363
Epoch 2/40
218/218 [==============================] - 27s 123ms/step - loss: 0.3630 - accuracy: 0.8593 - precision: 0.8865 - recall: 0.8288 - auc: 0.9651 - f1_score: 0.8479 - val_loss: 6.2628 - val_accuracy: 0.3503
Epoch 3/40
218/218 [==============================] - 28s 126ms/step - loss: 0.2490 - accuracy: 0.9044 - precision: 0.9196 - recall: 0.8861 - auc: 0.9829 - f1_score: 0.8975 - val_loss: 4.3876 - val_accuracy: 0.3435
Epoch 4/40
218/218 [==============================] - 30s 139ms/step - loss: 0.1678 - accuracy: 0.9366 - precision: 0.9455 - recall: 0.9283 - auc: 0.9919 - f1_score: 0.9326 - val_loss: 3.9004 - val_accuracy: 0.4027
Epoch 5/40
218/218 [==============================] - 29s 132ms/step - loss: 0.1551 - accuracy: 0.9436 - precision: 0.9495 - recall: 0.9372 - auc: 0.9928 - f1_score: 0.9401 - val_loss: 5.8703 - val_accuracy: 0.3173
Epoch 6/40
218/218 [==============================] - 27s 121ms/step - loss: 0.1218 - accuracy: 0.9555 - precision: 0.9602 - recall: 0.9511 - auc: 0.9951 - f1_score: 0.9530 - val_loss: 3.8994 - val_accuracy: 0.4043
Epoch 7/40
218/218 [==============================] - 28s 127ms/step - loss: 0.1017 - accuracy: 0.9625 - precision: 0.9658 - recall: 0.9598 - auc: 0.9965 - f1_score: 0.9602 - val_loss: 8.2409 - val_accuracy: 0.3052
Epoch 8/40
218/218 [==============================] - 28s 130ms/step - loss: 0.0764 - accuracy: 0.9725 - precision: 0.9758 - recall: 0.9690 - auc: 0.9978 - f1_score: 0.9709 - val_loss: 3.0719 - val_accuracy: 0.5905
Epoch 9/40
218/218 [==============================] - 27s 124ms/step - loss: 0.0815 - accuracy: 0.9715 - precision: 0.9748 - recall: 0.9687 - auc: 0.9975 - f1 score: 0.9694 - val loss: 3.8332 - val accuracy: 0.5155
```

Fig 5: Model.fit()




```
test_results = model.evaluate(test_dataset)

150/150 [==============================] - 15s 100ms/step - loss: 0.5953 - accuracy: 0.9093 - precision: 0.9103 - recall: 0.9082 - auc: 0.9639 - f1_score: 0.9008
```

Fig 6: Model's Evaluation Metrics Visualization

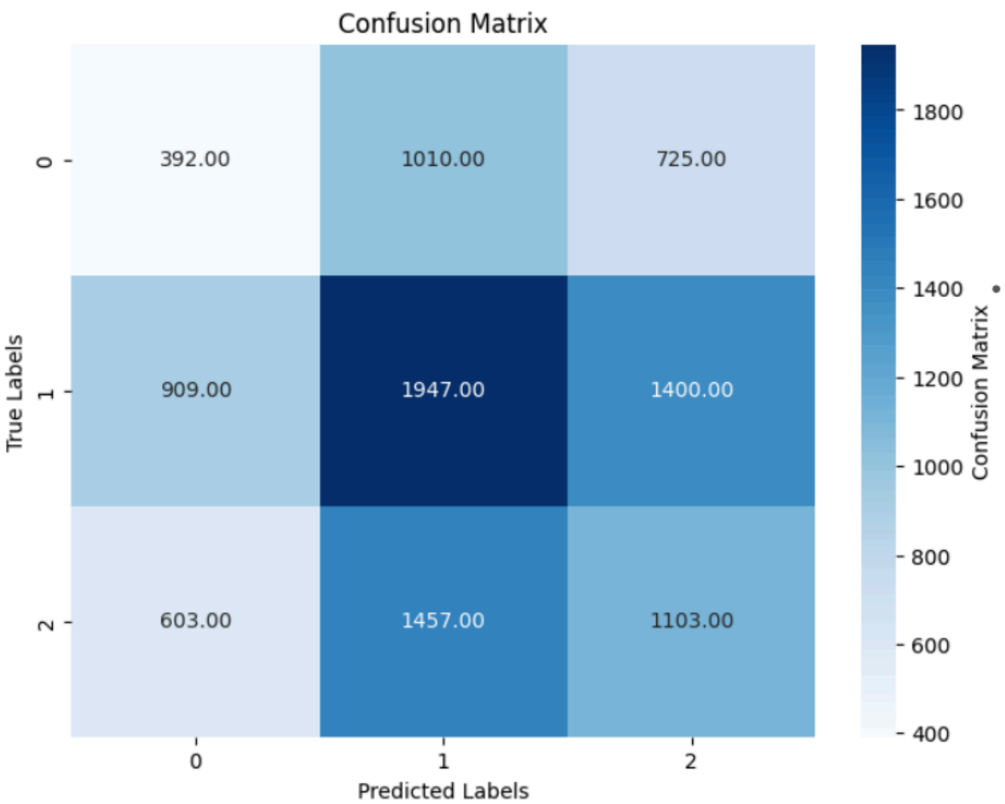


Fig 7: Model's Confusion Matrix

8. Conclusion and Future Scope

This paper achieves an accuracy of 62.52% on FER 2013 dataset and 90.93% on the Human Emotions Dataset. We thoroughly tune the hyperparameters and try many optimizers and learning rate schedulers as well as early stopping. We plan to implement data augmentation, novel loss functions, and the incorporation of attention mechanisms into pre-trained models. Furthermore, we aim to explore new datasets to propel our model's performance forward.

9. References

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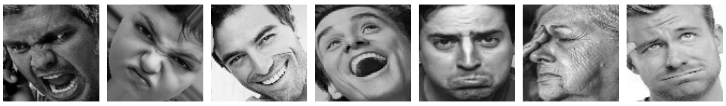
10. Annexures

10.1 Dataset Images

10.1.1 FER 2013

10.1.2 Human Emotions Dataset



11. Similarity Report

R&D Final Report

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