# ANALYZING FACIAL EMOTION PATTERNS IN AFFECTNET WITH DEEP NEURAL NETWORKS

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I, Sagar Uniyal hereby certify that the work which is being presented in the thesis entitled "Analyzing Facial Emotion Patterns in AffectNet with Deep Neural Networks" in partial fulfilment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Information Technology, Delhi Technological University is an authentic record of my own work carried out during the period from 2022 to 2024 under the supervision of Dr. Ritu Agarwal.

The work presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

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# Analyzing Facial Emotion Patterns in AffectNet with Deep Neural Networks

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## ABSTRACT

The significance of emotion recognition and its potential benefits are explored in the research. Emotion recognition is crucial as it enhances our understanding of human affect and facilitates improved interactions between humans and machines. The study underscores the importance of accurately identifying emotions in various fields, including stress detection in person, user experience design, human-computer interaction, and social robotics.

The research employs the AffectNet dataset, a large-scale repo of facial images equipped with emotion categories specifically to train and examine deep neural network models. Specifically, Convolutional Neural Networks (CNNs) are used due to their efficiency of effectively analysis tasks in image. The models are carefully designed as well as fine-tuned to handle the variety and complex nature of the AffectNet dataset, Handling issues such as changing stances, clarity, and face limitations.

The work provides a comparison of several CNN designs and their performance in emotion identification tasks. Each model's strengths and limitations are evaluated using evaluation criteria like as accuracy, precision, recall, and the F1-score. The results of this comparison work will help to improve the accuracy and efficiency of emotion identifying systems.

The results of the research give useful information on the effectiveness of different CNN models in recognising facial emotions. Such results can help to develop emotion identification system, making them more useful in real-world scenarios. Furthermore, the work provides to the area of deep learning by identifying practical problems and solutions for training models on large and heterogeneous datasets such as AffectNet. The findings improve our knowledge of human emotions and establish the framework for future advances in personalised applications, therapeutic tools, and human-machine interactions.

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# CHAPTER 1
# INTRODUCTION

Emotion recognition is useful in many types of applications which includes interaction between humans as well as computers, stress health monitoring, and affective computing. Although human emotions are complex and variable but precisely recognising and understanding them from facial expressions is difficult and complex. Deep Neural Networks (DNNs) have emerged as strong tools and technique in solving these difficulties because of their ability to automatically extract high-level features from raw data.[1] DNNs may enhance the accuracy of emotion identification tasks drastically when trained on very big datasets like AffectNet. The benefits of using DNNs include their ability to learn complicated patterns and adapt to new data, and is effective against previously encountered situations which makes them ideal for emotion identification tasks. Below figure illustrates the diversity and range of emotions as seen in Figure 1.1

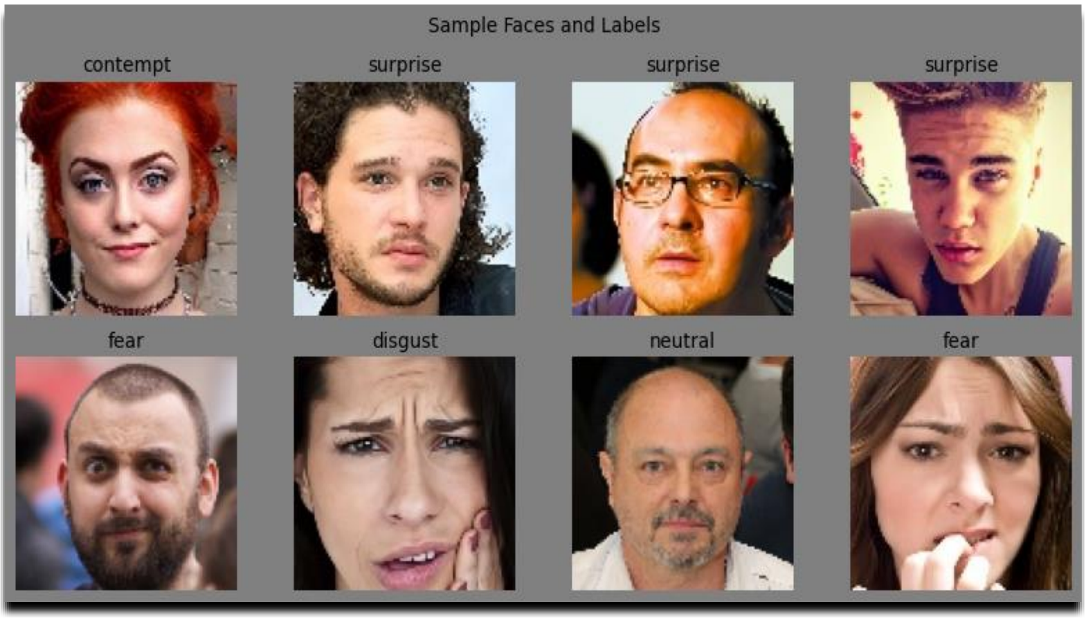



Figure 1.1: Sample Faces of various emotion class

This thesis aim is to deep dive into the application of Convolutional Neural Networks (CNNs) on the huge dataset like AffectNet for emotion recognition which highlights the usefulness and potential of deep learning techniques in enhancing emotion recognition accuracy. AffectNet is one of the vastest face emotion datasets available globally which provides a huge rich source of data with over one million annotated facial photos which covers a wide spectrum of emotions.[13] The use of these CNNs which a specialized type of DNN can particularly beneficial for this task because of their proficiency in image related tasks and feature extraction. Through rigorous and deep training and evaluation, CNNs can be able to identify subtle and complex differences inside facial expressions therefore improving the precision of emotion classification. This thesis will explore various CNN architectures, assess their performance, and to discuss the implications as well as limitation of using deep learning for emotion recognition. By doing this we aim to contribute to the advancement of affective computing and to provide insights into the development of a robust and accurate emotion recognition systems.

## 1.1 Challenges in emotion recognition

Emotion recognition is a vital aspect of human communication which often relies on facial expressions to convey basic feelings during interactions.[2] However to accurately identify emotions from facial expressions presents numerous challenges due to the complexity of human emotions through face which can vary widely across individuals and cultures. Factors like lighting, pose, occlusions, and individual differences in expressing emotions can significantly differ and affect the accuracy of recognition systems.[3]

Recent research delves into utilizing deep neural networks like Convolutional Neural Networks (CNNs), Convolutional Recurrent Neural Networks (CRNNs), and Gated Recurrent Units (GRUs) for speech emotion recognition.[1] These technologies have significantly enhanced the performance and faster emotion identification from speech, shedding light on the challenges and advancements in this field.[5] The integration of audio and visual data for emotion recognition, while promising, introduces additional complexities such as synchronizing and effectively merging multimodal inputs.

Furthermore, the development of new models, such as "ConvNet," based on convolutional neural networks, has shown promise in detecting various emotions through facial expressions.[4] These models showcase the tabular or hierarchical feature extraction capabilities of CNNs to identify patterns that have intricate details in facial expressions that are indicative of different emotional states. However, despite these advancements, challenges remain in creating models that can generalize well across diverse and unseen datasets, maintain robustness in real-world conditions, and address ethical concerns regarding privacy and bias.[6]

Given the critical implementation of deep learning technologies in Emotion Recognition, various applications have eventuated, namely: Feedback Analysis, Face Unlocking, and Mental Health Monitoring. The works are on the development of emotion recognition systems with developed technologies, which will further advance the user experience in terms of better, more personal, and more responsive interaction at the same time proposed for application in security and education. However, research on high-precision and reliable emotion recognition systems is still underway. The work currently conducted will try to develop possible improvements over the existing potential for improvement and practical implications that would promise significant advances in understanding and interacting with human emotions in this digital age.

### 1.2 Improving Emotion Recognition Accuracy with Deep Neural Networks

Emotion is one of the classic successes of deep neural networks, specially in the context of speech and facial expression.[3] Emotion, through interaction, is one-way human beings have always communicated. It is the highly advanced state of the technology that allows the development of complex models, like CNNs, CRNNs, and GRUs, for speech emotion recognition, and hence sets the benchmark higher for accuracy and efficiency in the identification of emotions expressed during speech. Therefore, many researchers have now entered into such a complex manner of recognition of emotions in speech and facial expressions through deep learning techniques. More precisely, new models like ConvNet have been developed with the appearance of convolutional neural networks for future applications in the existing domain of detecting and interpreting the various emotions expressed on faces, marking breakthroughs for the automatic recognition domain of facial emotion through deep learning techniques [3]. Emotion recognition is characterized by introducing deep learning methodologies that make it ready to be deployed in a wide range of real-world applications, from feedback analysis to face-unlocking systems. Advanced deep neural networks combine technologies for amalgamated emotion recognition, which increases the rate and precision of the systems, thus bringing human-computer interaction together with emotional intelligence to a new level.

### 1.3 Advantages of using deep neural networks for ER

Emotion recognition using DNNs has a long list of benefits, especially for speech and facial expressions.[9] Emotions have played a very vital role in human communication, which can often be shared with facial expressions performed using a simple conversation with the human being [1]. It has been well proven to use deep neural networks like CNN, CRNN, and GRU in the recognition of speech emotion, and this approach has been identified to give better accuracy and latency in recognizing emotions [2]. Still more profound, the general embedding of deep learning technology has dramatically improved the recognition of emotions by speech, which shows the importance of implementing more advanced systems that should give more accurate and more evident results. More recently, several studies have been focused on the development of such an automatic emotion recognition system for accurate detection of some facial expressions, such as the ConvNet model of the face. When put together, these abilities allow the deep neural network to fabricate an emotion recognition scheme supporting the remaining application—feedback analysis and face unlocking. Such an approach has demonstrated the capability of deep learning in task performance about emotion recognition.

The utilization of deep neural networks basically used for emotion recognition using the AffectNet dataset as well as Convolutional Neural Networks (CNN), has showcased the significant of growth mostly in the domain of HCI interactions and emotional intelligence.[4] The research mostly highlights the transformative impact of deep learning technologies which include CNN, CRNN, and GRU which in enhancing emotion recognition systems speech as well as for facial expressions. By using the capabilities of deep neural networks, researchers have successfully developed automatic emotion recognition systems that shows the high accuracy and efficiency. The introduction of models like the ConvNet, based on convolutional neural networks, has demonstrated promising results in detecting diverse emotions through facial expressions, further emphasizing the potential for innovation in this field.[4] Through the amalgamation of advanced deep neural networks and emotion recognition technologies, the accuracy and efficiency of emotion recognition systems have significantly improved, paving the way for practical applications in special areas such as feedback analysis and face unlocking. The discussion section of this research could further elaborate on the implications of these findings for human-computer interactions, potential limitations of the research, and suggestions for future research directions.

# CHAPTER 2
# LITERATURE SURVEY

Previously there have been many studies done on the implementation of machine learning and deep learning in emotion classification.

In one of the research, Ben Niu et al. [1] used a combination of Support Vector Machines (SVM) with Local Binary Patterns (LBP) and ORB features to enhance facial emotion recognition on JAFFE, CK+, and MMI datasets, showing notable improvements in accuracy. This study highlights the effectiveness of integrating traditional machine learning techniques with advanced feature extraction methods.The author of Fernandez et al. [2] suggests a unique approach i.e FERAtt: Facial Expression Recognition with Attention Net on CK+ dataset. In another approach Pranav et al. [4] suggests a deep neural network approach using a two convolutional layer. More specifically (J wang et al.) explores a better approach of shallow neural networks to identify emotions based on speech methods.

M A Almulla et al. [6] offer a multimodal approach by utlilizing dep nerual network on MER dataset which is based on video which seamlessly integrate text, and audio and video files to identify emotions. In order to classify emotions based on AffectNet dataset Sanjeev Roka et al. [7] using the fined tuned vision transformer using analysis of human machine teaming. For real time identifying emotions A Dowd et al. [8] proposed the use of machine learning models using the edge computing for detecting and classifying emotions by utlilizing the FER2013, JAFFE, KDEF, and CK+ dataset. The vectorized facial features can also be used to identifying the emotion, for which G yang et al. [9] suggests a deep neural technique. In another study, Loan Trinh et al. used the IEMOCAP corpus, a dataset featuring emotions expressed in videos, to apply deep neural networks for emotion recognition. M Singh et al. [11] also suggests Video DNN on IEOMCAP corpus to identify emotions. In one of the study Wafa et al. [15] proposed an accurate method for identifying the facial emotions by ultilizing the wavlet technique on deep neural network.

Despite the considerable spike in the research of identifying emotions, the focus has shifted towards the usage of deep neural networks for identifying emotions Qian Jiang et al. [12] suggests two streams of interclass network for identifying the emotions applying on FER 2013 and ck+ dataset.

The overview of the comprehensive literature review, along with their Methods and dataset used, is presented in Table

Table 2.1: Summarized review of literature papers

| | AUTHORS | METHODS | DATASET |
|---|---|---|---|
| **[1]** | Niu Ben et al. | SVM+LBP+ORB | JAFFE<br>CK+<br>MMI |
| **[2]** | M Fernandez et al. | FERAtt | CK+ |
| **[3]** | SNonis et al. | 3D approaches | BU-3DFE |
| **[4]** | Pranav et al. | DCNN | - |
| **[5]** | Jian Wang et al. | Deep and shallow network | - |
| **[6]** | Almulla | DCNN | MER |
| **[7]** | Sanjeev Roka et al. | Vision Transformer | - |
| **[8]** | Ashley Dowd et al. | ML techniques | FER2013<br>AFFECNET<br>JAFFE<br>CK+ |
| **[9]** | Guojun Yang et al. | DNN with vectorized features | CK+ |

| | | | |
|---|---|---|---|
| **[10]** | Loan Trinh Van et al. | DNN | IEMOCAP |
| **[11]** | Mandeep Singh | Audio and Video DNN (CNN, RNN) | IEMOCAP |
| **[12]** | Qian Jiang | Interclass Variation enhancement network | FER2013 CK+ |

# CHAPTER 3
# PROBLEM DEFINITION AND SCOPE

## 3.1 Problem Statement

The analysis of facial expressions has advanced very significantly thorughout recent years, mainly because of the developments of deep learning. AffectNet, which is a huge collection of images of faces and which is labelled with emotion classifications, is a very excellent resource for this purpose. Deep neural networks, which is particularly a Convolutional Neural Networks (CNNs), may be used to detect and interpret face expression patterns with great accuracy.[4]

This thesis addresses the difficulty of monitoring some face emotion patterns in AffectNet using deep neural networks. Basically, we use CNNs to detect and understand basic yet complex face features that are correspond to various emotions. The goal is to increase the ability of emotion detection systems to identifying emotion correctly through which are used in a variety of sectors including between interaction of humans and computers, stress health evaluation, and marketing.

Through this research, we hope to expand our knowledge that how deep learning models may be used to complicated datasets like AffectNet to detect some varied emotion patterns. Basically, we want to improve the flexibility and precision of emotion detection by just improving CNN architectures and doing experimenting with the help of different training approaches. Our study just helps us to build simpler and responsive algorithms so that we can make a better approach to rad human emotions through system.

## 3.2 Goal and Objective

- **Complexities of facial emotion recognition**

  The goal of this study is to investigate the basic yet complex patterns of face emotions using Convolutional Neural Networks (CNNs) with the help of the huge library of emotion files i.e. AffectNet dataset. By looking into this the interpreting small features that relate to diverse emotional states, this study hopes to increase our knowledge on the emotion detection and the accuracy of systems can be recognised in these emotions.

- **Improve emotion detection to further interaction between humans and computers**

  This work seeks to contribute to the creation of more responsive and transparent interaction between humans and computers systems by improving emotion detection algorithms using deep learning. Emotion recognition may enhance user experience and engagement in applications like virtual assistants, interactive gaming, and customer service.

- **Enhance mental health assessment and monitoring**

  The study final aims to use deep learning models effectively to improve mental health evaluation and monitoring while doing any medication. Reliable detection and analysis will keep in mind to make of facial expressions can help in healthcare sector to diagnose and track emotional state of well-being of person, providing a non-invasive and fast approach of mental health assessment.

- **Develop robust emotion recognition models for diverse applications**

  A very basic objective is to develop a dependable emotion detection model so that it may be used in a variety of sectors, including marketing, privacy, and entertainment. By optimising this CNN architectures and we are testing various training approaches so the project intends to construct the very adaptable so the models that function properly in numerous real-world circumstances.

- **Create a user-friendly emotion detection system**

  The study's goal is to create a simple yet sturdy system that helps people to simply upload photographs samples or may be videos and to evaluate emotional content by analzying the samples. By designing such an easy interface and by applying advanced deep learning algorithms, the project aims to allow people to understand and interpret emotional just by uploading the picture, improving media literacy and fostering informed interactions in digital settings.

# CHAPTER 4

## METHODOLOGY

In the Methodology part we will be discussing about the dataset used, process flow and different model used in the coding part. We can start by discussing about the dataset used.

### 4.1 Dataset Used

The dataset used in this research is AffectNet which is downloaded from Kaggle. AffectNet is a huge collection of facial images starred with "affects," which defines as to psychological facial expressions. To address basic limitations of memory the resolution of each image was dropped down to 96x96 pixels while ensuring uniform image dimensions across the dataset. This pre-processing step definitely helps in saving the computational resources effectively while preserving the essential features of images which required in late stages of emotion recognition.[13]

As shown in Table 4.1, the dataset images are categorized into eight different classes, each representing specific affective states: anger, contempt, disgust, fear, happy, neutral, sad, and surprise. Each class has many numbers of photos which represent a wide variety of expressions and emotions gathered from different sources. These sources include social media, news articles, and web videos.

Table 4.1: Number of Images per Emotion Class

| Emotion | Number of Images |
|---|---|
| **Anger** | 3,218 |
| **Contempt** | 2,871 |
| **Disgust** | 2,477 |
| **Fear** | 3,176 |
| **Happy** | 5,044 |
| **Neutral** | 5,126 |
| **Sad** | 3,091 |
| **Surprise** | 4,039 |
| **Total** | 29,042 |

The number of photos per class reflects extensive collection of samples. The largest categories are neutral and cheerful, both with over 5,000 photos, ensuring a substantial sample size for these emotions. Other classes, such as rage, fear, and surprise, include significant representations, providing that the model can learn to recognise these emotions correctly. The dataset's diverse sources and rich annotations make it an invaluable resource for developing and testing deep learning models for face emotion identification. Each image depicts a unique emotional state, demonstrating the dataset's capacity to facilitate comprehensive emotion analysis.[13]

This study takes advantage of AffectNet's dataset which is well-structured which is best for building and test a strong Convolutional Neural Networks (CNNs) for facial emotion identification. The dataset's is annotations well and wide coverage of diverse emotional classes definitely ensure that the models get trained well on it which may generalise the goodness to real-world settings therefore increasing the findings' applicability and dependability.

### 4.2 Proposed Workflow

The workflow diagram illustrates our research steps which get begins with the gathering of the AffectNet dataset from Kaggle source.

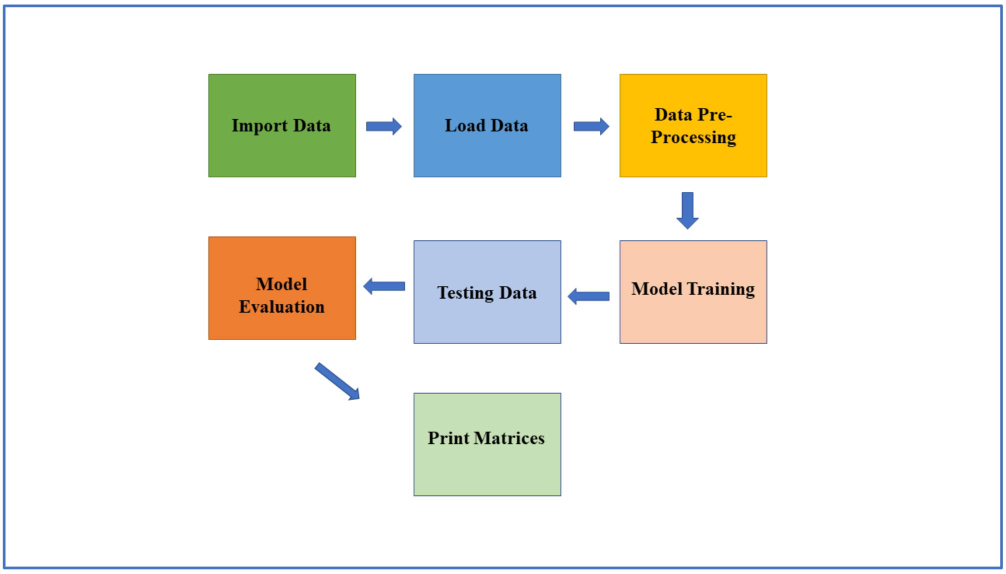



Figure 4.2: Workflow

We have focused on this data, using Convolutional Neural Network models to check the model effectiveness on performance criteria, as seen in Figure 4.2.

1. **Import Data**

   The initial stage in our process is to basically import the dataset, which is a huge collection of facial images starred with "affects," which defines as to psychological facial expressions. AffectNet's broad and diverse images samples make it a best resource for training DL models. Using Python packages, we have converted the info and samples data into a well-structured manner which is appropriate for analysis. This phase helps us to read the picture sample files and their labels to ensure that the data is easily get available for later stages.

2. **Load Data**

   Second step is importing the data into memory. This step involves arranging the sample photos and their emotion labels in a way that it can be easily input into the CNN models. This strategy helps not only optimizing memory use but also promotes the efficiency of the data handling process, ensuring that the models receive data in the necessary format for optimal training.

3. **Data Pre-processing**

   The dataset's training and validation samples are scaled to 96x96 pixels and RGB formatted to guarantee consistency and compatibility with the CNN models. The dataset has a slightly biased training set. The limitation in the distribution of emotion classes might make it difficult to train the model, since some emotions may be under stapled in comparison to others classes. To address this, we have used all available examples for certain classes while subset of the samples for others, which were more common. This strategy helps us to balance the training process, ensuring that the model learns to identify all emotion categories accurately and performs well in real-world applications.[7]

4. **Model Training**

   The fundamental focus of this research is model training. We train three different CNN models and compare their performance in recognising facial emotions. Each model is carefully constructed with a specific architecture, then built and trained with the training data. The models use layers of convolutional, pooling, and dense processes to capture hidden face expression patterns. During training, the models learn how to relate input photos to emotion labels while reducing categorical cross-entropy loss, a popular objective function for multi-class classification problems. This process requires repeated iterations (epochs) over the training data, allowing the models to gradually modify their internal parameters for increased accuracy.

5. **Testing Data**

   Following training, it is critical to evaluate the models on a separate testing dataset to determine their generalised skills. The test dataset, which is separate from the training and validation sets, offers a fair baseline for evaluating the model's performance in real-world circumstances. This stage includes using trained models to predict the emotion labels of test pictures and comparing those predictions to the ground truth labels. The test set evaluation verifies that the models do not overfit to the training data and can accurately recognise emotions in previously viewed photos.

6. **Model Evaluation**

   Complete model assessment involves determining a variety of indicators of performance to analyse and compare the effectiveness of trained models. Figure 4.3 depicts key measures like as accuracy, precision, recall, and F1-score, which together give better details how into the model's classification performance.

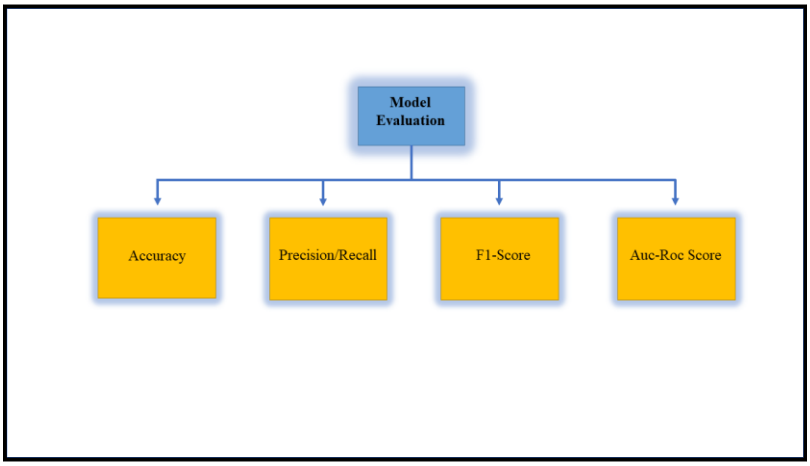



Figure 4.3: Model Evaluation Matrices

Moreover, confusion matrices are used to visualise the models' performance across several emotion classes, highlighting areas of strength and possible development. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is also used to check the models' ability to differentiate between various emotion classes. This thorough approach confirms that the models are properly evaluated and that their strengths and weaknesses are fully accepted.

7. **Print Matrices**

Finally, the assessment indicators are organised and presented to enable an extensive evaluation of the three CNN models. This comprises producing the classification report, confusion matrix, and AUC-ROC curve for every model. The classification report summarises the precision, recall, and F1-scores for each emotion class, whilst the confusion matrix shows a visual comparison between the model's predictions and actual labels. The AUC-ROC curve provides further validation of the models' performance at various threshold levels. By showing these measurements, we can identify the best-performing model and pinpoint particular areas for development.

### 4.3 Proposed Model

We have used and applied three different Convolutional Neural Network (CNN) models to identify the face emotion patterns in the AffectNet dataset. Each model gets through rigorous training and testing to assess its ability to identify the facial emotions. After carefully studying the emotion classification, we propose the three-model due to its adaptability in various criteria. The following is a full overview of CNNs, the three models employed, and the reasoning behind suggesting the third model.

### 4.3.1 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning model that best in processing and analysing visual data. CNNs are intended to automatically and adaptively learn spatial features of information from input samples.[4] They are made up of various layers which are distinct apply various function on images:

1. **Convolutional Layers:** These layers are most important part of CNN which apply convolutional filters to the input samples images, creating feature maps that identify the various features on image such as edges, textures, and patterns. Each filter helps us to detects specific features at various spatial locations in the image sample. For instance, an edge-detection filter helps in highlighting the boundaries of objects in the image.[4]
2. **Activation Functions:** Activation functions introduces non-linearity into the model, allowing it to learn complex patterns. Common activation functions are like ReLU (Rectified Linear Unit), which sets all the values which are below the zero line i.e.  negative values to zero, and SELU (Scaled Exponential Linear Unit), which helps in maintaining self-normalizing properties The SELU activation function aids in the preservation of self-normalizing features, ensuring that the network maintains consistent activations throughout the layers, resulting in improved learning and convergence.
3. **Pooling Layers:** Also known as subsampling or down sampling layers because pooling layers helps in reduce the dimensionality of each feature map by preserving the most useful information across a certain area which minimizing computational complexity. Common techniques of max pooling are picking the highest value in a window, and average pooling which helps us to computes the average value.
4. **Batch Normalization:** Batch normalization layers help maintain equilibrium and speed up the learning process. This technique helps us to improve the speed of training by giving the input in batch which is normalized by this layer.

5. **Dropout Layers:** Dropout is a regularization technique that prevents overfitting by randomly disabling some fraction of neurons during training. Dropout layers help us to prevent overfitting by randomly drop some neurons during training, which definitely helps in the model to learn more features.
6. **Fully Connected Layers:** After the convolutional and pooling layers the layer which comes is fully connected layers which are used to combine features and make predictions.[4] These layers connect every neuron in one layer to every neuron in the next layer means that it converts the 2d matrix into one dimensional, integrating the extracted features to classify the input image.

### 4.3.2 First Model

The first CNN model served as the foundation for our experiments. This model has a very basic design, with a few convolutional and pooling layers followed by fully linked layers, as seen in Figure 4.4. While it worked pretty well, with reasonable accuracy and dependability, it had certain problems when recognising less common emotions such as scorn and disgust. The model's simplicity, although useful for computing speed, hampered its capacity to capture complex face traits.

This CNN (convolutional neural network) model consists of multiple layers that progressively extract and learn features from the input image. The model starts with a conv2d input layer that accepts an image of shape (None, 96, 96, 3), where None represents the batch size, and the remaining dimensions are height, width, and channels (RGB) of the input image. It then passes through several convolutional (conv2d) layers that apply filters to extract low-level and high-level features. After each conv2d layer, there is a batch normalization layer for stabilizing training and a max pooling layer for spatial down sampling. Dropout layers are also included to remove the overfitting. The model has multiple sets of these conv2d, batch normalization, and max pooling layers with increasing numbers of filters, allowing it to learn more complex features. Finally, the output of these layers is flattened and passed through fully connected (dense) layers, with another batch normalization and dropout layer before the final dense layer with 8 output units, potentially for an 8-class classification task.

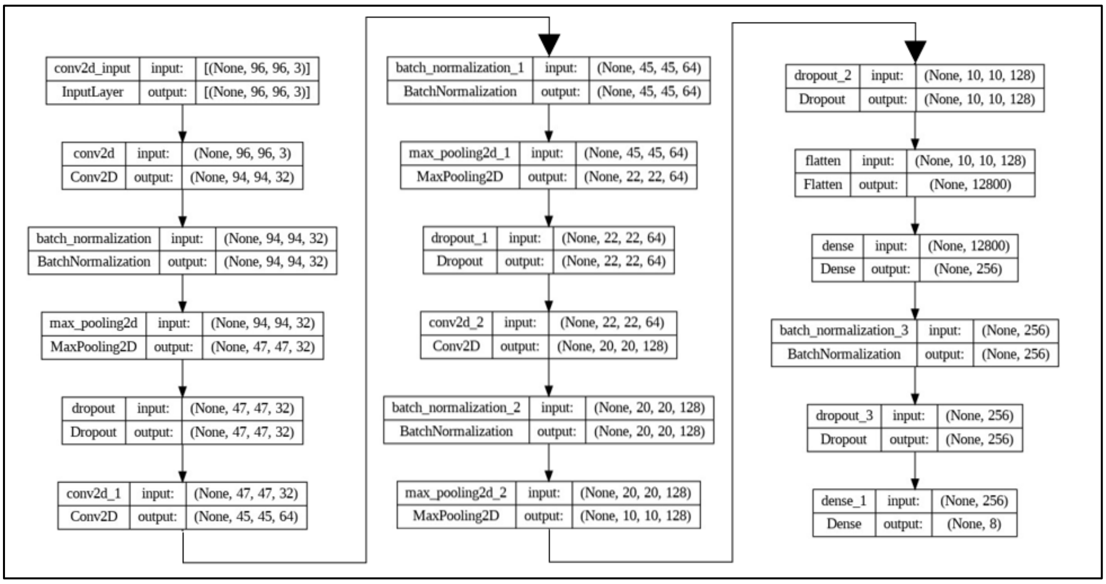



Figure 4.4: Model 1

### 4.3.3 Second Model

The second model included a more complicated architecture, including more convolutional layers and complexity. This change improved the model's capacity to learn more detailed patterns in the data, resulting in greater performance compared to the first model, as seen in figure 4.5. Despite the additional complexity, this model still struggled to achieve high accuracy for specific emotions and showed overfitting tendencies during training, as indicated by the performance difference between training and validation.

This CNN model starts with an input layer that accepts the image data. It then passes through a series of convolutional layers that apply filters to extract low-level and high-level features from the input image. After each convolutional layer, there is a batch normalization layer to stabilize the training process and a max pooling layer to downsample the spatial dimensions of the feature maps. Dropout layers are also incorporated to prevent overfitting by randomly dropping out a fraction of the input units during training. The model alternates between convolutional, batch normalization, max pooling, and dropout layers, with the number of filters increasing in the later convolutional layers to capture more complex features. Finally, the output of these layers is flattened into a 1D vector and passed through fully connected (dense) layers, with additional batch normalization and dropout layers, to produce the final output predictions. The architecture of this model allows it to hierarchically extract and combine features from the input image, while incorporating techniques like normalization and dropout to improve training stability and prevent overfitting.

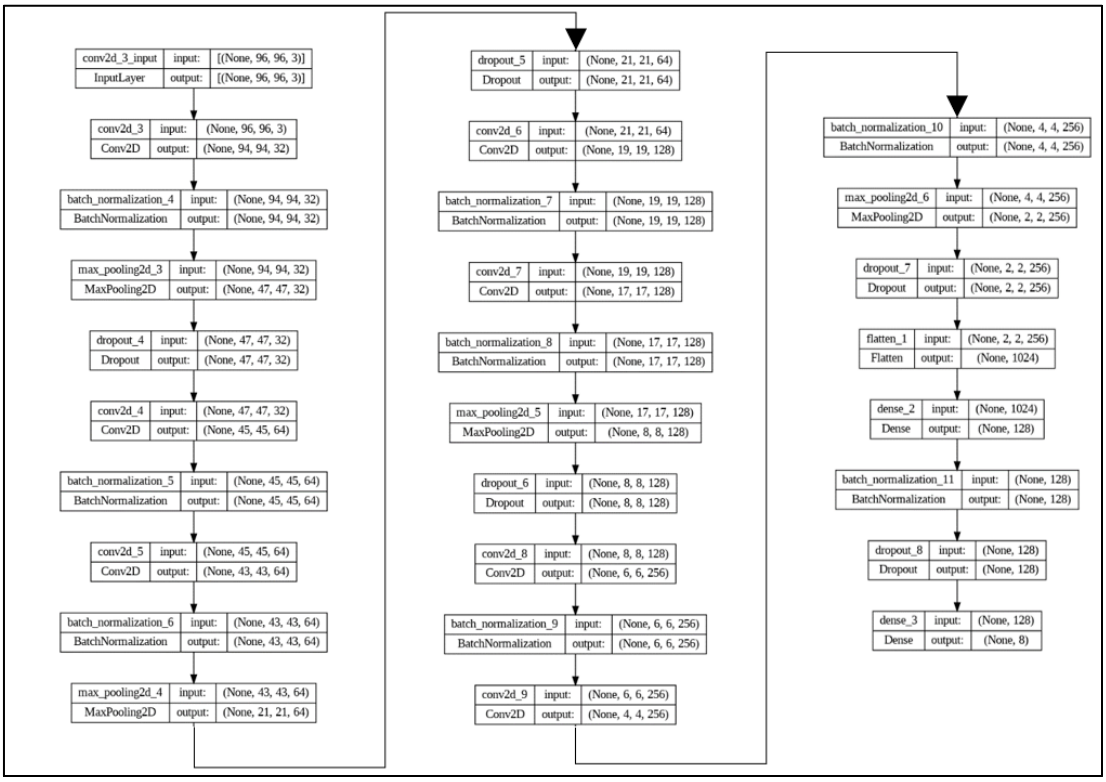



Figure 4.5: Model 2

### 4.3.4 Third Model

The third CNN model, which we suggest, integrates advanced methodologies and architectural improvements to solve the drawbacks of the prior models. To maintain and speed up the learning process, this model comprises multiple advanced convolutional blocks, regularisation dropout layers, and batch normalization. These modifications result in enhanced generalisation and robustness, as evidenced by the assessment metrics.

The proposed model’s architecture is illustrated in Figure 4.6. The model uses seven convolutional layers. The first convolutional layer applies filters to the input image. The input shape is (None, 96, 96, 3), and the output shape is (None, 94, 94, 32). The layer has 32 filters, and the spatial dimensions have been reduced due to the convolution operation. Next is the Batch Normalization layer, which normalizes the output of the previous convolutional layer to aid in training stability and convergence. Following that is a max-pooling layer that down samples the input by taking the maximum value in each window size of (2,2). The output shape of this layer is (None, 47, 47, 32). Then, a dropout layer randomly drops 30% of input weights to prevent overfitting. Afterward, another convolutional layer with 64 filters produces an output image of shape (None, 45, 45, 64). This is followed by a batch normalization layer. This process repeats three times, except for the last iteration where the last two layers are omitted. The final output shape after this process is (None, 2, 2, 256). A Flatten layer is used to convert the 4D input tensor (batch, height, width, channels) into a 2D tensor (batch, features) with shape (None, 1024). Then, a fully connected (dense) layer with 128 output units follows, resulting in an output shape of (None, 128). Batch normalization is applied to this fully connected layer, followed by a dropout layer on its output. Lastly, the final dense layer has 128 output units, resulting in an output shape of (None, 8), corresponding to the 8 classes for classification. The final layer of the neural network employs the SoftMax activation function, which converts the raw outputs into a probability distribution where each value represents the model's estimated likelihood that the input belongs to a particular class.

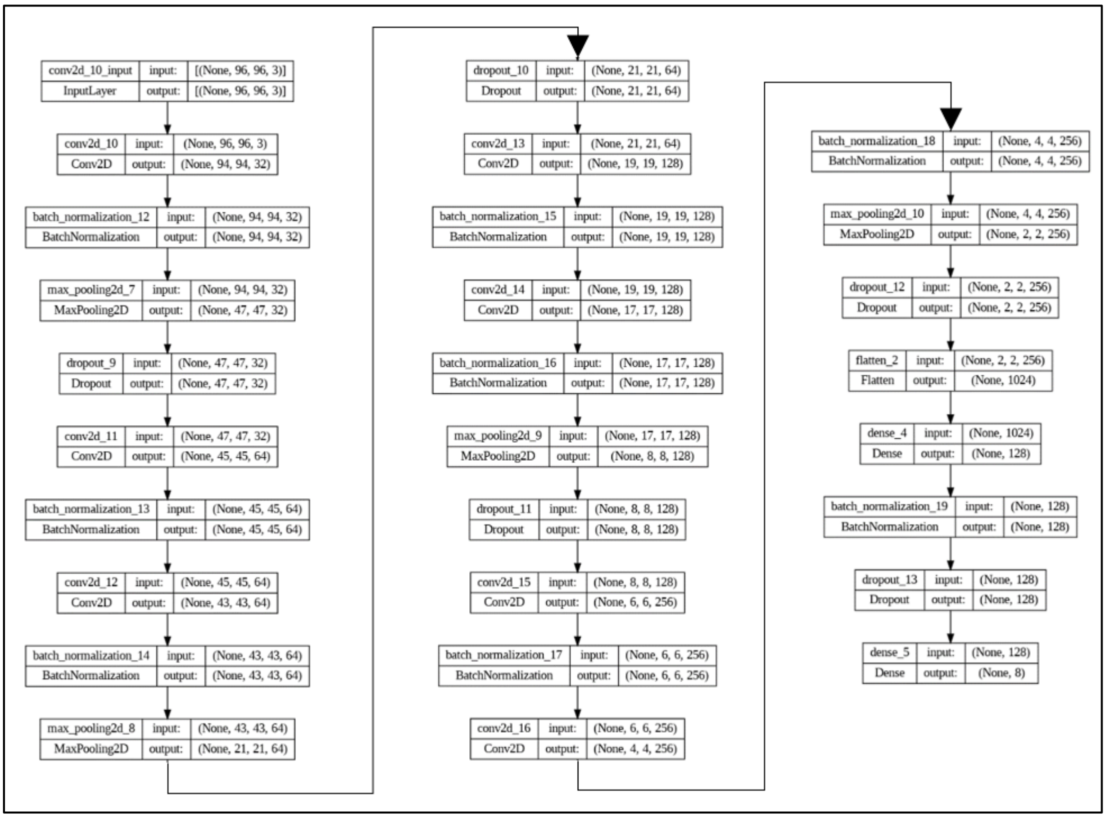



Figure 4.6: Third Model

Key features of the third model include:

- **Advanced Convolutional Layers:** Utilizing deeper and more complex convolutional layers enables the model to capture fine-grained details in facial expressions.
- **SELU Activation Function:** The SELU activation function aids in the preservation of self-normalizing features, ensuring that the network maintains consistent activations throughout the layers, resulting in improved learning and convergence.
- **Regularization Techniques:** Dropout layers help us to prevent overfitting by randomly drop some neurons during training, which definitely helps in the model to learn more features.
- **Batch Normalization:** This technique helps us to improve the speed of training by giving the input in batch which is normalized by this layer.

The third model performs bests among three the models in terms of accuracy, precision, recall, and F1-score. It is also observed that model 3 definitely better at identifying all emotion classes with higher results specially like as contempt and disgust. The confusion matrix and AUC-ROC curves expressed its ability to identify patterns in facial emotion.

# CHAPTER 5

## RESULT AND DISCUSSION

After evaluating each proposed model performance on the AffectNet dataset and optimizer used as Adam and categorical cross-entropy as the loss function, we have produced various evaluation metrics like accuracy, classification report and auc score to assess each model's effectiveness in identifying patterns of emotions. The Adam optimizer was chosen because of its variable learning rate capabilities which definitely helps in improving the training process, and the categorical cross-entropy loss function is suitable for classification type problem which has more than one class.

We used evaluation metrics such as accuracy, precision, recall, F1-score, Confusion matrix and AUC-ROC curve which provides an overall evaluation on the model's performance for accurately detecting and distinguishing all emotion classes in the dataset. Accuracy is a measurement of the model's overall performance, while precision and recall are subtly different and provides more information on how the model is performing on each individual class. F1-score is a combined weighted average of precision and recall, which provides a fairer evaluation on the model's performance in classification. The confusion matrix provides an overall measurement for the performance of the model across all the classes it is trying to distinguish and the AUC-ROC curve evaluates the model's ability to differentiate between classes at different degrees of thresholds. These measurements are necessary to be able to analyse the model's weaknesses and strong points, and be able to determine which one of the face emotion identification methods is effective. Below is the comparison of every model's accuracy:

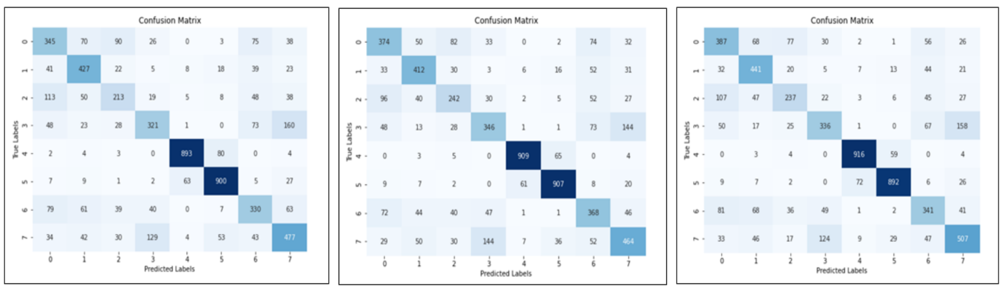
Table 5.1: Accuracy Comparison

| Model | Accuracy (%) |
|---|---|
| **Model 1** | 67 |
| **Model 2** | 69 |
| **Model 3** | 70 |

The accuracy table shows slightly yet better improvement on the models, with Model 3 performing best among the three. This improvement definitely showcases us that the architecture of model 3 is better than other two and also optimization function used in Model 3, such SELU (activation functions) and the best utilization of the Adam optimizer while applying categorical cross-entropy loss function helps model 3 to perform best among three.

Furthermore, we have built confusion matrix to evaluate the performance of models. Confusion matrices helps us to identify the true positive, false positive, true negative, and false negative values of every class. This allows us to perform a better analysis of which model is best at separating the emotional groups. By looking at the confusion matrices, we can identify the emotional classes that gave the model difficulties, and that the model handled well, and therefore provide a better characterisation and explanation of the classification performance issues.

Below, we have presented the confusion matrices of all three models as shown in figure 5.1 which allows us to give a direct comparison of each model's performance across the different emotion classes:




Confusion Matrix Model 1 Confusion Matrix Model 2 Confusion Matrix Model 3

Figure 5.1: Comparison of Confusion matrix of models

The confusion matrices from the three distinct CNN models show differences in performance across classes. Model 1 has very good accuracy for classes 5 and 4, with the majority of incorrect classifications happening in classes 3 and 7. Model 2 improves on this by lowering misclassifications in classes 2, 3, and 6, implying more generalisation and robustness across these categories. Model 3 improves accuracy, particularly in classes 0 and 3, while also retaining high performance in classes 4 and 5. Overall, Model 3 has a more balanced performance with fewer severe incorrect classifications than the other two models, implying that it is the most successful of the three in managing a wide variety of classes.

After this we further uses below evaluation metrics to compare the models, showcasing the performance of each model in detail:

- Precision is calculated by:

$$Precision = \frac{T_P}{T_P + F_P} \times 100 \quad - (1)$$

- Recall is calculated by:

$$Recall = \frac{T_P}{T_P + F_N} \times 100 - (2)$$

- F1-Score is calculated by:

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall \times Precision} \times 100 - (3)$$

Higher the F1-score, better the prediction rate. The capacity to discriminate between the various classes is represented by the AUC-ROC measure. The classifier's ability to distinguish between benign and malicious networks is stronger when the AUC-ROC value is higher. This number ought to be less than one and positive.

Table 5.2: Model 1 Classification Report

| Emotions/Metrics | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| **Anger** | 0.52 | 0.53 | 0.52 | 647 |
| **Contempt** | 0.62 | 0.73 | 0.67 | 583 |
| **Disgust** | 0.50 | 0.43 | 0.46 | 494 |
| **Fear** | 0.59 | 0.49 | 0.54 | 654 |
| **Happy** | 0.92 | 0.91 | 0.91 | 986 |
| **Neutral** | 0.84 | 0.89 | 0.86 | 1014 |
| **Sad** | 0.54 | 0.53 | 0.54 | 619 |
| **Surprise** | 0.57 | 0.59 | 0.58 | 812 |

Table 5.3: Model 2 Classification Report

| Emotions/Metrics | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| **Anger** | 0.57 | 0.58 | 0.57 | 647 |
| **Contempt** | 0.67 | 0.71 | 0.69 | 583 |
| **Disgust** | 0.53 | 0.49 | 0.51 | 494 |
| **Fear** | 0.57 | 0.53 | 0.55 | 654 |
| **Happy** | 0.92 | 0.92 | 0.92 | 986 |
| **Neutral** | 0.88 | 0.89 | 0.89 | 1014 |
| **Sad** | 0.54 | 0.59 | 0.57 | 619 |
| **Surprise** | 0.60 | 0.57 | 0.59 | 812 |

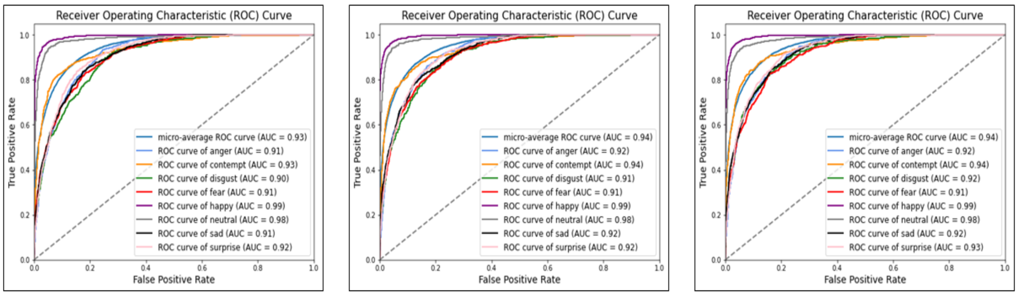
Table 5.4: Model 3 Classification Report

| Emotions/Metrics | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| **Anger** | 0.55 | 0.60 | 0.58 | 647 |
| **Contempt** | 0.63 | 0.76 | 0.69 | 583 |
| **Disgust** | 0.57 | 0.48 | 0.52 | 494 |
| **Fear** | 0.59 | 0.51 | 0.55 | 654 |
| **Happy** | 0.91 | 0.93 | 0.92 | 986 |
| **Neutral** | 0.89 | 0.88 | 0.88 | 1014 |
| **Sad** | 0.56 | 0.55 | 0.56 | 619 |
| **Surprise** | 0.63 | 0.62 | 0.63 | 812 |

After carefully examining the precision, recall and F1-Score, we have evaluated the models' performance by using AUC-ROC (Area Under the Receiver Operating Characteristic Curve) scores and curves. The AUC-ROC curve is useful for multi-class classification which showcase a model's ability to distinguish between classes across various thresholds. The AUC score, ranging from 0 to 1, indicates overall performance, with higher values signifying better discrimination.

The ROC curve which basically plots the curve of true positive rate (sensitivity) against the false positive rate (1-specificity) for each and every class, highlighting the trade-offs between them. Comparing the AUC-ROC curves and scores of the three models provides deeper insights into their ability to differentiate between emotion classes.

Below figure illustrated shows the AUC-ROC curves and scores of each model:




AUC-ROC CURVE of MODEL 1 AUC-ROC CURVE of MODEL 2 AUC-ROC CURVE of MODEL 3

Figure 5.2: Comparison of AUC_ROC curve

Table 5.5: Comparisons of AUC-ROC scores

| Model | Micro-average AUC | Anger | Contempt | Disgust | Fear | Happy | Neutral | Sad | Surprise |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.93 | 0.91 | 0.93 | 0.90 | 0.91 | 0.99 | 0.98 | 0.91 | 0.92 |
| **2** | 0.94 | 0.92 | 0.94 | 0.91 | 0.91 | 0.99 | 0.98 | 0.92 | 0.92 |
| **3** | 0.94 | 0.92 | 0.94 | 0.92 | 0.91 | 0.99 | 0.98 | 0.92 | 0.93 |

**Analysis and Comparison:**

- **Micro-average AUC**: Both Model 2 and Model 3 have a micro-average AUC of 0.94 which is slightly higher than Model 1's.
- **Class-specific AUC**: Model 3 performs better than the other two models in the two classes i.e. 'disgust' and 'surprise' classes having AUC scores of 0.92 and 0.93, respectively. Otherwise, model 3 performs similar to model 2.

- **Consistency**: Model 3 performs consistently better across all classes in auc scores which makes it a best choice among the three models for emotion identifying tasks.

Based on AUC-ROC curves and scores we recommend Model 3 as the best model among the three for identifying the patterns in facial emotions in the AffectNet dataset due to its very dense and deep rigorous training which makes its performance superior across all emotion classes.

Finally, we can conclude that Model 3 performs the best compared to the other models in every evaluation metrics. The accuracy, precision, recall, and F1 scores, as well as AUC-ROC curves all are better compared to other two models which demonstrate its resilience and accurateness. As a result, we recommend Model 3 as the best model compared to other two for identifying patterns in face emotion patterns in the AffectNet dataset. This model definitely works in the applications which requires to user's feedback and need of identifying the state of emotions like in health sectors.

# CHAPTER 6
# CONCLUSION AND FUTURE WORK

## 6.1 Conclusion

The study of facial expression patterns in AffectNet using deep neural networks has shown promising results specially in identifying the different emotions i.e.  anger, sorrow, happiness, disgust, and neutrality. We were able to identify the patterns in facial features from the AffectNet dataset by using a Convolutional Neural Network (CNN) architecture, which result in high-accuracy and predictions of emotional classes. The performance criteria, such as accuracy, precision, recall, F1 score, and confusion matrix and auc score elaborate our model’s performance.

Our model's ability to identify the relying patterns in emotion classes can greatly help in applications that are in dire need of sentiment analysis, stress detection, health monitoring, and HCI applications. Our model's robustness, along with very deep training on the AffectNet dataset, shows its practical applications in a wide range of scenarios, from normal feedback system to health monitoring.

## 6.2 Future Work

In future our study revolves around to expand the capabilities of our model by including better approach and multimodal and bimodal framework. Using both video with still photographs will likely to provide a more thorough approach of classifying emotions throughout time. The larger dataset can also help in better model training. Use of further enhanced deep learning techniques and various pretrained neural network might help to increase the model's accuracy.

Moreover, deep research in various areas will be done to confirm the usefulness of the model across different people and environments. This may involves collecting a bigger and more variety dataset, by improving the biasedness, and authenticating the model's adaptability in real-world scenarios.

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# LIST OF PUBLICATION

1. Sagar Uniyal and Ritu Agarwal, “Analyzing Facial Emotion Patterns in AffectNet with Deep Neural Networks” accepted in 1st IEEE International Conference on Advances in Computing, Communication and Networking- ICAC2N-24, (16th - 17th December 2024), Greater Noida, India.
2. Sagar Uniyal and Ritu Agarwal, “Unveiling Emotions: A Deep Dive into Inception V3-based Facial Emotion Detection using Transfer Learning” accepted in 1st IEEE International Conference on Advances in Computing, Communication and Networking- ICAC2N-24, (16th - 17th December 2024), Greater Noida, India.

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**Sagar Uniyal <sagar00uniyal@gmail.com>**

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1 message

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| **Conference Acronym:** | ICAC2N |
| **Start Date:** | 16-Dec-2024 |
| **End Date:** | 17-Dec-2024 |
| **Venue Name:** | ITS Engineering College |
| **City:** | Greater Noida |
| **State/Province:** | |
| **Country/Region:** | India |

### Submitter Information

| | |
|---|---|
| **Salutation:** | |
| **Given name/First name:** | Vishnu |
| **Middle name:** | |
| **Last/Family/Surname:** | Sharma |
| **Suffix:** | |

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# 1st International Conference on Advances in Computing, Communication and Networking (ICAC2N-2024)

**Conference Record Number # 63387**

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Received a sum of **Rs. 7000/-** from **Sagar Uniyal** of **Delhi Technological University (DTU)** as registration fee for **Paper ID – 876 "Unveiling Emotions: A Deep Dive into Inception V3-based Facial Emotion Detection using Transfer Learning"** in 1st IEEE International Conference, ICAC2N-2024, organized by Department of CSE, ITS Engineering College, Gr. Noida, India on 16th-17th Dec., 2024.

**Prof. (Dr.) Vishnu Sharma**

**Convener & Conference Organizing Chair**

**1st IEEE ICAC2N-2024**

ANNEXURE-IV

# DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi-42

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