Facial Expression Recognition Using Deep Learning

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COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the Thesis on **"Facial Expression Recognition Using Deep Learning"** is a bonafide work of Harsh Mata, Harshal Dhunde, Chirag Bamb, Ved Agrawal submitted to the Rashtrasant Tukdoji Maharaj Nagpur University, Nagpur in partial fulfillment of the award of a Bachelor of Technology, in Computer Science and Engineering has been carried out at the Department of Computer Science and Engineering, Shri Ramdeobaba College of Engineering and Management, Nagpur during the academic year 2022-23.

Date: 06 June 2023

Place: Shri Ramdeobaba College of Engineering and Management, Nagpur.

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DECLARATION

I, hereby declare that the thesis titled **"Facial Expression Recognition Using DeepLearning"** submitted herein, has been carried out in the Department of Computer Science and Engineering of Shri Ramdeobaba College of Engineering & Management, Nagpur. The work is original and has not been submitted earlier as a whole or part for the award of any degree/diploma at this or any other institution / University.

Date: 06 June 2023

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Approval Sheet

This Project report entitled "**Facial Expression Recognition Using Deep Learning**" by Harsh Mata, Harshal Dhunde, Chirag Bamb, Ved Agrawal is approved for the degree of Bachelor of Technology.

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Place: Shri Ramdeobaba College of Engineering and Management, Nagpur.

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ABSTRACT

Facial expression recognition plays a crucial role in understanding human emotions and behavior, and it has gained significant attention in the field of computer vision. In this project, we focus on developing a facial expression recognition system using deep learning techniques. Our objective is to accurately classify facial expressions into distinct emotion categories such as happiness, sadness, anger, surprise, fear, and disgust.

To achieve this, we employed Convolutional Neural Networks (CNNs), a powerful deep learning architecture known for its effectiveness in image analysis tasks. We trained various CNN models using two popular facial expression datasets: the RAF (Ryerson Audio-Visual Database of Emotional Speech and Song) dataset and the FER (Facial Expression Recognition) dataset. These datasets contain a diverse range of facial images with annotated emotion labels.

For training the models, we experimented with different CNN architectures, including variations of popular networks like VGGNet, ResNet, and Inception. Each architecture was fine-tuned and trained on the various datasets.

Through rigorous experimentation and hyperparameter tuning, we achieved promising results. Our best-performing model achieved a training accuracy of 98% and a testing accuracy of 93% on the RAF dataset, with the Conv5 model. This indicates the model's ability to accurately classify facial expressions and generalize well to unseen data.

Overall, this project demonstrates the successful application of deep learning techniques for facial expression recognition. The developed models exhibit impressive performance, with high accuracy achieved on the RAF dataset. The findings of this project can have significant implications in fields such as human-computer interaction, affective computing, and psychology, enabling improved understanding and interpretation of human emotions from facial expressions.

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CHAPTER 1

INTRODUCTION

In today's interconnected world, human-computer interaction has become an integral part of our daily lives. As technology continues to advance, there is a growing need for systems that can understand and respond to human emotions effectively. Facial expression recognition, a prominent area of research in the field of computer vision, holds tremendous potential for bridging the gap between humans and machines by enabling devices to perceive and interpret human emotions accurately.

This report delves into the fascinating domain of facial expression recognition, exploring its significance, methodologies, challenges, and potential applications. Through extensive research and analysis, we aim to provide a comprehensive overview of the current techniques, shed light on their limitations, and propose innovative solutions to enhance the accuracy and robustness of facial expression recognition systems.

The ability to recognize and interpret facial expressions is a fundamental aspect of human communication. Our faces effortlessly convey a wide range of emotions, including happiness, sadness, anger, surprise, fear, and disgust, among others. While humans possess an innate ability to decipher these subtle cues, designing algorithms that can emulate this capability is a complex task. Facial expression recognition systems aim to bridge this gap by leveraging computer vision techniques and machine learning algorithms to automatically analyze and interpret facial expressions from images or video sequences.

The applications of facial expression recognition are diverse and encompass a multitude of domains. From improving human-computer interaction in fields such as gaming, virtual reality, and robotics to revolutionizing healthcare by aiding in diagnosing and treating mental health disorders, the potential impact of this technology is immense. Additionally, facial expression recognition can also be harnessed for security and surveillance purposes, enabling enhanced emotion-based threat detection and identification.

However, the development of accurate and reliable facial expression recognition systems faces several challenges. These include variations in lighting conditions, pose, occlusions, individual differences, and the inherently subjective nature of human emotions. Addressing these challenges necessitates the exploration and implementation of advanced techniques such as deep learning, convolutional neural networks, and facial feature extraction algorithms.

Throughout this report, we will explore various methodologies used in facial expression recognition, ranging from traditional approaches to the state-of-the-art deep learning models. We will critically analyze their strengths and weaknesses, discuss relevant datasets and evaluation metrics, and propose potential avenues for future research and development. By gaining a deeper understanding of the intricacies involved in facial expression recognition, we can pave the way for more accurate, and reliable systems.

In conclusion, this report aims to provide a comprehensive overview of the field of facial expression recognition, highlighting its importance, challenges, and potential applications. By decoding the complex web of emotions encoded in human facial expressions, we endeavor to contribute to the advancement of technology that can better understand and empathize with human emotions, fostering more effective human-machine interaction and improving the quality of our digital experiences.

1.1 OBJECTIVE

The primary objective of this report is to present a comprehensive study of facial expression recognition (FER) techniques. The report aims to explore the effectiveness of different methodologies for accurately detecting and interpreting facial expressions from images or video sequences.

The report will focus on the following specific objectives:

1. To review and analyze traditional and state-of-the-art approaches for facial expression recognition, including feature extraction methods, machine learning algorithms, and deep learning architectures.
2. To evaluate the performance of different facial expression recognition algorithms on benchmark datasets, considering metrics such as accuracy, loss, etc.
3. To explore the potential applications of facial expression recognition in diverse domains, including human-computer interaction, healthcare, security, and entertainment.
4. To identify the limitations and challenges associated with facial expression recognition, such as the subjective nature of emotions and the need for large and diverse datasets, and propose avenues for future research and improvement.

By achieving these objectives, this report aims to provide a comprehensive analysis of facial expression recognition techniques, enabling readers to gain insights into the effectiveness, limitations, and potential applications of different algorithms. Additionally, it seeks to contribute to the advancement of facial expression recognition technology, fostering more accurate and emotionally intelligent systems for enhanced human-machine interaction.

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1.2 PROJECT REPORT OUTLINE

The following is an outline for the project report on facial expression recognition:

- Introduction
    - Background and motivation for the project
    - Objectives and Scope of the Report
- Literature Review
    - Background and prerequisites

    - Overview of existing approaches for facial expression recognition
    - Review of image processing techniques for facial expression recognition
    - Evaluation of different algorithms for facial expression recognition
- Implementation
    - Proposed methodology
    - Different methods used to train model
    - Image recognition and processing
    - User interface
    - Sample outputs
- Results and Discussion
    - Results of different models after training them based on training and validation accuracy
    - Metrics for comparison based on training and testing accuracy
    - Result
- Conclusion and Future Work
    - Summary of the key findings of the study
    - Concluding remarks on the effectiveness of image processing techniques for solving Sudoku puzzles
    - Future directions for research in this area
- References
    - List of sources cited in the report

CHAPTER 2

BACKGROUND AND PREREQUISITES

Facial expression recognition (FER) is a captivating field of study within computer vision, aiming to enable machines to understand and interpret human emotions conveyed through facial expressions. Facial expressions serve as vital communicative cues in human interactions, conveying a wide range of emotions such as happiness, sadness, anger, surprise, fear, and disgust. While humans possess a natural aptitude for interpreting these expressions, designing algorithms that can replicate this capability presents a complex challenge. FER systems utilize image processing techniques and machine learning algorithms to analyze facial features and classify them into distinct emotional categories. By leveraging these technologies, FER holds significant potential in diverse domains, including enhancing human-computer interaction, revolutionizing healthcare diagnostics, and improving security and surveillance measures. To delve into the study of FER, a strong foundation in computer vision, image processing, and machine learning is crucial, accompanied by proficiency in programming languages, knowledge of relevant datasets, familiarity with feature extraction and classification algorithms, and an understanding of the different facial expressions and their corresponding emotional states.

2.1 INTRODUCTION TO FACIAL EXPRESSION RECOGNITION

Facial expression recognition (FER) is a captivating field of study within computer vision, aiming to enable machines to understand and interpret human emotions conveyed through facial expressions. Facial expressions serve as vital communicative cues in human interactions, conveying a wide range of emotions such as happiness, sadness, anger, surprise, fear, and disgust. While humans possess a natural aptitude for interpreting these expressions, designing algorithms that can replicate this capability presents a complex challenge. FER systems utilize image processing techniques and machine learning algorithms to analyze facial features and classify them into distinct emotional categories. By leveraging these technologies, FER holds significant potential in diverse domains, including enhancing human-computer interaction, revolutionizing healthcare diagnostics, and improving security and surveillance measures.

2.2 UNDERSTANDING FACIAL EXPRESSIONS

Facial expressions are an integral part of human communication, enabling the expression of emotions and intentions. They involve various components, including the movement of facial muscles, changes in facial geometry, and alterations in facial textures. A range of emotions can be conveyed through facial expressions, each characterized by specific patterns and combinations of muscle movements. Common facial expressions include happiness, characterized by a smile and raised cheeks; sadness, featuring a downturned mouth and lowered eyebrows; anger, involving a furrowed brow and tightened lips; surprise, marked by widened eyes and an open mouth; fear, showcasing widened eyes, raised eyebrows, and a tensed face; and disgust, identifiable through a wrinkled nose and raised upper lip. Recognizing and interpreting these expressions accurately is crucial for machines to understand human emotions and respond appropriately [6].

2.3 IMAGE PROCESSING TECHNIQUES IN FER

FER systems rely on image processing techniques to extract meaningful information from facial images. These techniques involve various steps, including face detection, face alignment, feature extraction, and classification. Face detection algorithms locate and identify faces within an image, allowing subsequent analysis to focus on the relevant region. Face alignment techniques normalize facial images by aligning them based on landmarks such as the eyes, nose, and mouth. This alignment compensates for variations in pose and scale, ensuring consistency across different faces. Feature extraction involves capturing relevant facial characteristics, such as shape, texture, and appearance. Common approaches include using geometric features, local binary patterns (LBP), and histograms of oriented gradients (HOG). Finally, the extracted features are input to machine learning algorithms for classification, which can include traditional methods like Support Vector Machines (SVM) or more advanced deep learning models like Convolutional Neural Networks (CNN).

2.4 FER ALGORITHMS AND MODELS

Numerous algorithms and models have been developed for facial expression recognition. These include traditional machine learning approaches such as SVM, k-Nearest Neighbors (k-NN), and Random Forests, which utilize handcrafted features and manual feature selection. Additionally, deep learning models like CNNs have demonstrated remarkable performance in FER tasks, allowing for end-to-end learning of features and classification. Models such as VGGNet, ResNet, and InceptionNet have been adapted and trained on large facial expression datasets, achieving state-of-the-art accuracy in emotion recognition. Transfer learning techniques have also been employed, where pre-trained models on large-scale image datasets are fine-tuned on facial expression data, leveraging the learned representations[2].

2.5 PREREQUISITES FOR BUILDING A FER SYSTEM

Before delving into the development of a facial expressions recognition (FER) system, it is essential to consider the following prerequisites:

- **Understanding of Facial Anatomy and Expressions:** A solid understanding of facial anatomy, including the arrangement and movements of facial muscles, is crucial. Familiarity with various facial expressions and their corresponding muscle movements is necessary to accurately interpret and classify emotions [4][6].

- **Image Processing and Computer Vision:** Proficiency in image processing techniques and computer vision algorithms is vital for analyzing facial images. This includes knowledge of image filtering, feature extraction, and image segmentation methods to extract relevant facial features[5][6].

- **Machine Learning and Deep Learning:** Understanding machine learning concepts and algorithms is crucial for training models to recognize facial expressions. Familiarity with classification algorithms, such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and deep learning models like Convolutional Neural Networks (CNN), is necessary for achieving accurate emotion classification.

- **Programming Skills:** Proficiency in programming languages like Python is necessary for implementing FER algorithms and models. Knowledge of relevant libraries and frameworks, such as OpenCV, TensorFlow, or PyTorch, is beneficial for efficient development.

- **Data Acquisition and Annotation:** Acquiring a diverse dataset of facial expressions and accurately annotating them with corresponding emotions is critical. Understanding data collection methods, potential biases, and strategies for data augmentation is essential for creating a representative and balanced dataset [1][5].

- **Evaluation Metrics and Performance Analysis:** Familiarity with evaluation metrics for classification tasks, such as accuracy, precision, recall, and F1 score, is necessary to assess the performance of the FER system. Knowledge of techniques like cross-validation and confusion matrix analysis helps in robust performance analysis.

- **Ethical Considerations:** Developing an FER system requires awareness of ethical considerations surrounding privacy, consent, and potential biases. Ensuring the responsible use of facial expression data and addressing algorithmic biases is crucial to promote fairness and inclusivity.

By fulfilling these prerequisites, one can build a reliable and accurate FER system that effectively recognizes and interprets facial expressions across various applications and domains.

CHAPTER 3

LITERATURE SURVEY

3.1 RESEARCH PAPERS

A lot of research has been done in this field. Following are some of the research papers which will be discussed for a better understanding of the importance, uses, problems and requirements .

- A paper by Shan Li and Weihong Deng, 2018 [1] With the transition of facial expression recognition(FER) from laboratory- controlled to challenging in- the-wild conditions and the recent success of deep literacy ways in colorful fields, deep neural networks have increasingly been abused to learn discriminative representations for automatic FER. Recent deep FER systems generally concentrate on two important issues: overfitting caused by a lack of sufficient training data and expression-unconnected variations, similar as illumination, head disguise and identity bias. In this paper, we give a comprehensive check on deep FER, including datasets and algorithms that give perceptivity into these natural problems. First, we introduce the available datasets that are extensively used in the literature and give accepted data selection and evaluation principles for these datasets. We also describe the standard channel of a deep FER system with the affiliated background knowledge and suggestions of applicable executions for each stage. For the state of the art in deep FER, we review new deep neural networks and affiliated training strategies that are designed for FER grounded on both stationary images and dynamic image sequences, and bandy their advantages and limitations. Competitive performances on extensively used marks are also epitomized in this section. We also extend our check to fresh affiliated issues and operation scripts. Eventually, we review the remaining challenges and corresponding openings in this field as well as unborn directions for the design of robust deep FER systems.

- Facial Expression Recognition Based on Deep Learning : review and insight by Wafa Mellouka* , Wahida Handouzi [2] several areas similar as safety, health and in mortal machine interfaces. With the remarkable success of deep literacy, the different types of infrastructures of this fashion are exploited to achieve a better performance. The purpose of this paper is to make a study on a recent workshop on automatic facial Expression recognition FER via deep literacy. We accentuate these benefits, the armature and the databases used and we present the progress made by comparing the proposed styles and the results attained. The interest of this paper is to serve and guide experimenters by review recent workshop and furnishing perceptivity to make advancements

- Facial Expression Recognition Based on Deep Learning Convolution Neural Network: by Sharmeen M. Saleem Abdullah1*, Adnan Mohsin Abdulazeez [3], Facial Expression processing is one of the most important conditioning in effective computations, engagement with people and computers, machine vision, videotape game testing, and consumer exploration. Facial expressions are a form of verbal communication, as they reveal a person's inner passions and feelings. expansive attention to Facial Expression Recognition(FER) has lately been entered as facial expressions are considered. As the fastest communication medium of any kind of information. Facial expression recognition gives a better understanding of a person's studies or views and analyzes them with the presently trending deep literacy styles. delicacy rate sprucely compared to traditional state- of- the- art systems. This composition provides a brief overview of the different FER fields of operation and intimately accessible databases used in FER and studies the rearmost and current reviews in FER using complication Neural Network(CNN) algorithms. Eventually, it's observed that everyone reached good results, especially in terms of delicacy, with different rates, and using different data sets, which impacts the results

- PTZ-Camera-Based Facial Expression Analysis using Faster R-CNN for Student Engagement Recognition by E. Komagal and B. Yogameena, 2020 [4] During the epidemic, online classes are predominant. still, the new normal requirements effective analysis of scholars ’ classroom engagement. Offline classes also have a implicit trouble to scholars ’ engagement before and especially after thepost-covid. Facial Expressions Analysis has come essential in the literacy terrain, whether it's online or offline. The offline classroom terrain is considered a problem terrain. Since, it can be fluently acclimated to the online terrain. specially, in the PTZ camera terrain, the recognition becomes more grueling due to varying face acts, limited Field- of- View(FOV), illumination conditions, goods of the nonstop visage, drone- heft, and drone- eschewal. In this paper, facial expression- grounded pupil engagement analysis in a classroom terrain is proposed. Face discovery has been achieved by YOLO(You only look formerly) sensor to find multiple faces in the classroom with maximum speed and delicacy. Accordingly, by espousing the Ensemble of Robust Constrained Local Models(ERCLM) system, corner points are localized in detected faces indeed in occlusion, and thus, point matching is performed. either, the matched corner points are aligned by an affine metamorphosis. Eventually, having different expressions, the aligned faces are fed as input to Faster R- CNN(Faster Regions with Convolutional Neural Network). The proposed approach is demonstrated using the TCE classroom datasets and Online datasets. The proposed frame outperforms the state- of- the- art algorithms

- A Comprehensive Survey on Deep Facial Expression Recognition: Challenges, Applications, and Future Guidelines, authors, Muhammad Sajjad a, Fath U Min Ullah b , Georgia Christodoulou c , Faouzi Alaya Cheikh a, Mohammad Hijji d , Khan Muhammad e, Joel J.P.C. Rodriguesf,g (2021) [5] Facial expression recognition (FER) is an emerging and multifaceted research topic. Applications of FER in healthcare, security, safe driving, and so forth have contributed to the credibility of these methods and their adoption in human-computer interaction for intelligent outcomes. Computational FER mimics human facial expression coding skills and conveys important cues that complement.speech to assist listeners. Similarly, FER methods based on deep learning and artificial intelligence (AI) techniques have been developed with edge modules to ensure efficiency and realtime processing. To this end, numerous studies have explored different aspects of FER. Surveys of FER have focused on the literature on hand-crafted techniques, with a focus on general methods for local servers but largely neglecting edge vision-inspired deep learning and AI-based FER technologies. To consider these missing aspects, in this study, the existing literature on FER is thoroughly analyzed and surveyed, and the working flow of FER methods, their integral and intermediate steps, and pattern structures are highlighted. Further, the limitations in existing FER surveys are discussed.datasets are investigated in depth, and the associated challenges and problems are discussed. In contrast to existing surveys, FER methods are considered for edge vision (on e.g., smartphone or Raspberry Pi, devices, etc.), and different measures to evaluate the performance of FER methods are comprehensively discussed.

- "Fine-Grained Facial Expression Analysis Using Dimensional Emotion Model", 2021 [6] Automated facial expression analysis has a variety of applications in human-computer interaction. Traditional methods mainly analyze prototypical facial expressions of no more than eight discrete emotions as a classification task. However, in practice, spontaneous facial expressions in a naturalistic environment can represent not only a wide range of emotions, but also different intensities within an emotion family. In such situations, these methods are not reliable or adequate. In this paper, we propose to train deep convolutional neural networks (CNNs) to analyze facial expressions explainable in a dimensional emotion model. The proposed method accommodates not only a set of basic emotion expressions, but also a full range of other emotions and subtle emotion intensities that we both feel in ourselves and perceive in others in our daily life. Specifically, we first mapped facial expressions into dimensional measures so that we transformed facial expression analysis from a classification problem to a regression one.

CHAPTER 4

Dataset

4.1 Worked Dataset

We have worked on different combinations and sizes of Dataset “ Raf-DB” And “FER-2013”.
following are the datasets

- FER-2013 : The Facial Expression Recognition 2013 (FER-2013) dataset is a widely used resource in the field of facial expression recognition research. Created by Pierre-Luc Carrier and Aaron Courville, FER-2013 provides an extensive collection of grayscale images, each measuring 48x48 pixels. Comprising 35,887 images, the dataset offers a diverse range of facial expressions, classified into seven emotion classes: anger, disgust, fear, happiness, sadness, surprise, and neutral. To label the dataset, crowd-workers were engaged to annotate the images based on the emotions portrayed.
  FER-2013 has played a significant role in the development and evaluation of deep learning models for facial expression recognition. It has served as a benchmark dataset, enabling researchers to assess the performance of various algorithms and techniques in this domain. However, it is important to note certain limitations of FER-2013 this limitation are explained in [1][5][2]. The dataset was collected from the internet, which introduces noise and inaccuracies in labeling. Additionally, the images are of relatively low resolution, and the dataset may not fully capture the diversity of facial expressions in real-world scenarios. Despite these limitations, FER-2013 has been instrumental in advancing the field of facial expression recognition. Researchers have leveraged this dataset to investigate and develop novel approaches for emotion classification, fostering advancements in deep learning and computer vision techniques. As a valuable resource for the academic community, FER-2013 has served as a starting point for numerous research studies, facilitating the exploration of facial expression recognition in both theoretical and practical

applications. In conclusion, FER-2013 has significantly contributed to the understanding and development of facial expression recognition models. Its availability has spurred innovation and enabled researchers to push the boundaries of emotion analysis in images. However, researchers should be aware of its limitations and consider augmenting the dataset or utilizing other resources to address the potential shortcomings of FER-2013. Detailed explanations are given in [1].

- FER-2013 With 13000 images: the above mentioned FER-2013 is processed and we created new dataset with 13000 image with same specifications.
- FER-2013 With 13000 images and size 100X100 : the processed dataset again processed and made image size of 100X100 pixels
- RAF-DB : The RAF-DB (Ryerson Audio-Visual Database of Emotional Speech and Song) dataset is a valuable resource in the field of facial expression recognition, specifically focusing on facial expressions associated with emotional speech and song [1][5]. Developed by Lucey et al., RAF-DB provides a diverse collection of images with high variability. The dataset comprises 12,271 images, encompassing seven emotion categories: neutral, happy, sad, angry, fearful, surprise, and disgust. The images were obtained by capturing video recordings of actors who were instructed to express specific emotions while uttering emotional speech or singing. RAF-DB offers several advantages for facial expression recognition research. Firstly, it provides a wide range of emotional expressions in a controlled environment, ensuring consistent labeling. Secondly, the dataset captures both subtle and intense expressions, allowing for the analysis of nuanced emotions. Lastly, RAF-DB incorporates variations in lighting conditions, facial poses, and occlusions, simulating real-world scenarios[1].Researchers in the field have leveraged RAF-DB to develop and evaluate facial expression recognition algorithms, particularly those aimed at understanding emotional cues in speech and song. The dataset's complexity and high variability enable the exploration of robust models that can handle diverse facial expressions and environmental factors.It is important to note that RAF-DB, like any dataset, has its limitations. While it provides a rich collection of emotional expressions, the dataset predominantly features East Asian actors,

potentially limiting its generalizability to other populations. Additionally, the dataset's relatively small size may pose challenges for training deep learning models that require large amounts of data.Nonetheless, RAF-DB has emerged as a valuable resource for advancing research in facial expression recognition, particularly within the context of emotional speech and song. Its diverse and controlled nature enables researchers to study and develop models that are more capable of handling real-world scenarios and improving our understanding of emotional communication.In conclusion, RAF-DB serves as an important dataset for facial expression recognition, specifically focusing on emotions expressed through speech and song. Its rich variability and controlled environment make it a valuable asset for exploring and advancing the field, despite its limitations. Researchers should consider complementing RAF-DB with other datasets to further enhance the generalizability and robustness of their models.

- RAF-DB(Alligned) With 48x48x3: Above dataset is cropped according to face of portion and resized it to 48x48x3
- RAF-DB(Alligned) With 100x100x3: Above dataset is cropped according to face of portion and resized it to 100x100x3
- RAF-DB(Alligned) With 255x255x3: Above dataset is cropped according to face of portion and resized it to 48x48x3
- RAF-DB(Alligned) With 48x48x3 and 5000 images: Above dataset is cropped according to face of portion and resized to 48X48x3 on selected 5000 images.
- RAF+FER with 48x48 with images 48000+ : Both FER and RAF dataset are merged and resized to 48X48

4.2 Other Dataset

- **EXPW :** EXPW (Expression in the Wild) is a substantial dataset designed for facial expression recognition in real-world conditions. Created by Zhang et al., EXPW offers a diverse collection of facial images with the aim of addressing the challenges posed by unconstrained environments. Comprising over 91,793 images, EXPW covers a wide range of expressions, including seven emotion categories: neutral, happiness, sadness, surprise, anger, disgust, and fear. The dataset was collected from publicly available images on the internet, ensuring a varied and representative sample of facial expressions encountered in everyday life. EXPW is specifically designed to simulate real-world conditions, capturing the complexities of unconstrained environments. The images exhibit diverse variations in illumination, occlusions, poses, and image quality. This realism allows researchers to explore and develop robust facial expression recognition models that can effectively handle the challenges of the wild.

- CK+ : The CK+ (Cohn-Kanade) dataset is a widely recognized and extensively used resource for facial expression recognition in controlled environments. Developed by Cohn and Kanade, CK+ provides a comprehensive collection of facial images, accompanied by precise annotations of facial expressions.The dataset consists of 593 image sequences captured from 123 subjects, who were instructed to display specific facial expressions in a controlled setting. CK+ covers six emotion categories: neutral, happiness, sadness, surprise, anger, and disgust. Each image sequence in the dataset captures the temporal progression of the expressed emotion, enabling the analysis of dynamic facial expressions.CK+ offers several advantages for facial expression recognition research. It provides high-quality images with accurate annotations, facilitating the training, evaluation, and comparison of different models. The controlled environment ensures consistent lighting conditions, poses, and facial expressions, reducing potential confounding factors

CHAPTER 5

IMPLEMENTATION

5.1 PROPOSED METHODOLOGY

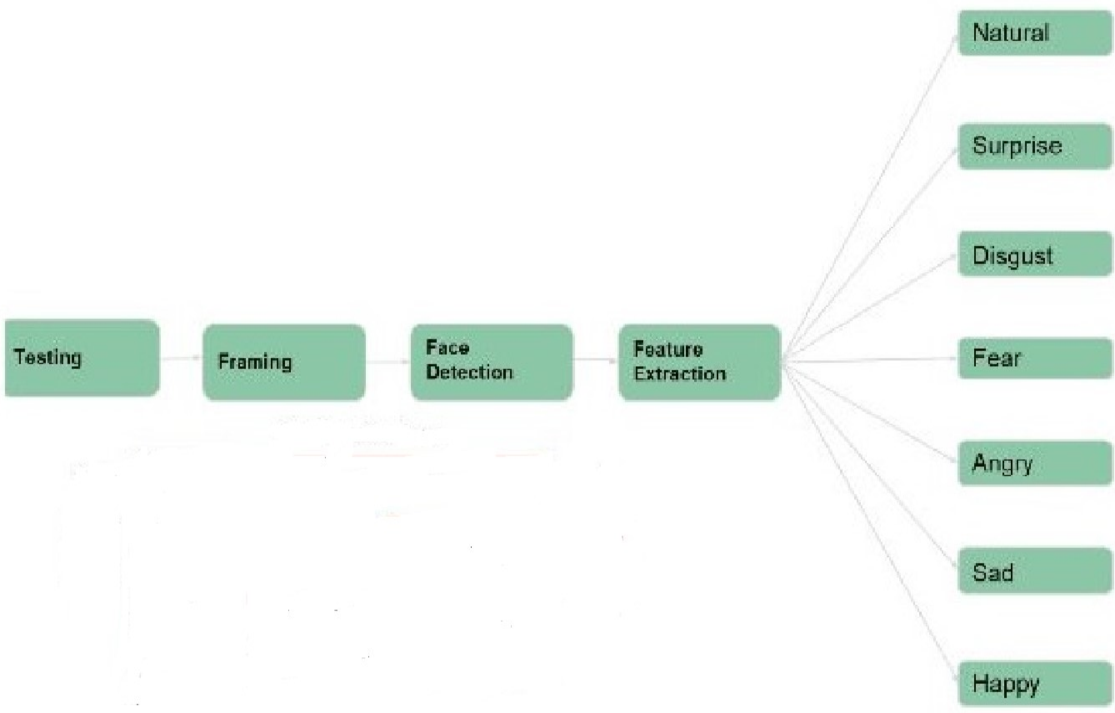


Fig 5.1 METHODOLOGY

The proposed methodology for facial expression recognition consists of six main steps:

The proposed methodology involves:

1. Collect dataset: The 1st step involves the collection of datasets that are already available publicly for facial expressions recognition. Some proposed datasets are FER2013 (containing grayscale images) or

creating our own dataset by capturing the images of different people with different types of expressions.

2. Pre-process dataset: After the collection of the dataset, the next step is to pre-process it, which involves cropping images in order to focus on the face, fixing the size i.e. resizing them, and finally converting them to RGB or grayscale.

3. Train a model: To train the model using the datasets after pre-processing and using Convolutional Neural Networks (CNN), which is a deep learning algorithm to train it as well as using transfer learning to train the model.

4. Test the model: After successful training of the model, we can test it on different types of datasets in order to check its performance or accuracy. Use of metrics such as precision and accuracy to measure the model's performanc e.

Deploy the model: Finally, after all the steps mentioned above, we will deploy the model to make predictions on new images. Also, the use of libraries such as OpenCV or TensorFlow can be done in order to integrate the model into our application or website.

5.2 DIFFERENT METHODS USED TO TRAIN MODELS

In this project, we have implemented mainly 2 different types for training the model:

5.2.1 Pretrained Model

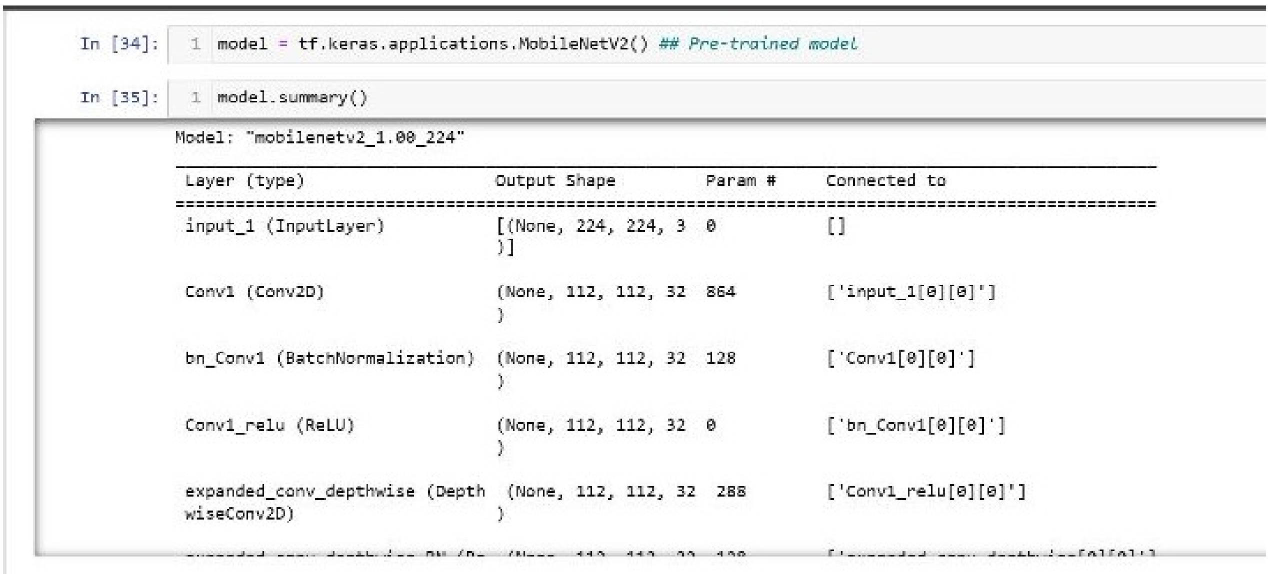
MobileNetV2 is a convolutional neural network architecture that is designed to be efficient and perform well on mobile devices. It is based on an inverted residual structure where the residual connections are between the bottleneck layers. The intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity. This architecture allows for efficient computation while still maintaining high accuracy in tasks such as image classification.

In the context of facial expression recognition, we have used MobileNetV2 as a pre-trained model for transfer learning. Transfer learning is a technique where a pre-trained model is fine-tuned on a specific task. In our case, the pre-trained MobileNetV2 model can be used as a feature extractor to extract relevant features from facial images. These features can then be fed into a classifier to detect different facial expressions.

The use of a pre-trained model such as MobileNetV2 can significantly reduce the amount of training data and time required to achieve high accuracy in facial expression recognition. This is because the pre-trained model has already learned to extract relevant features from images, and only the classifier needs to be trained on the specific task of facial expression recognition.

Overall, using MobileNetV2 as a pre-trained model for transfer learning in facial expression recognition can provide an efficient and accurate solution for this task.

We have used MobileNetV2 for transfer learning using the FER2013 dataset and achieved the relevant accuracy which is discussed in result and analysis.



```
In [34]:  1 model = tf.keras.applications.MobileNetV2() ## Pre-trained model

In [35]:  1 model.summary()

Model: "mobilenetv2_1.00_224"
_________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
=================================================================================================
 input_1 (InputLayer)           [(None, 224, 224, 3  0           []
                                )]

 Conv1 (Conv2D)                 (None, 112, 112, 32  864         ['input_1[0][0]']
                                )

 bn_Conv1 (BatchNormalization)  (None, 112, 112, 32  128         ['Conv1[0][0]']
                                )

 Conv1_relu (ReLU)              (None, 112, 112, 32  0           ['bn_Conv1[0][0]']
                                )

 expanded_conv_depthwise (Depth  (None, 112, 112, 32  288        ['Conv1_relu[0][0]']
 wiseConv2D)                    )
```

Fig 5.2 MobileNetV2

5.2.2 Build Model Using CNN architecture

In this architecture we mainly have 4 layers

1.Con2D layer - A Conv2D layer is a type of convolutional layer used in convolutional neural networks (CNNs). It performs a dot product between two matrices, where one matrix is the set of learnable parameters otherwise known as a kernel or filter, and the other matrix is the restricted portion of the receptive field[3]. The convolution operation involves sliding the filter over the input data and computing the dot product between the filter and the input data at each location. This produces a feature map that summarizes the presence of detected features in the input.

Conv2D layers are used to extract both low-level features such as lines and edges, as well as high-level features such as objects or parts of objects from images. These extracted features can then be used for tasks such as image classification or object detection.

2.MaxPooling2D layer - A MaxPooling2D layer is a type of pooling layer used in convolutional neural networks (CNNs). It performs a downsampling operation along the spatial dimensions of the input data by taking the maximum value over a sliding window of a specified size. This operation reduces the dimensionality of the input data while retaining the most important information.

MaxPooling2D layers are typically added to CNNs after individual convolutional layers[3]. They help to reduce the number of parameters and computation in the network, and also make the model more robust to variations in the position of features in the input image.

3.Flatten Layer -A Flatten layer is used in convolutional neural networks (CNNs) to convert the multi-dimensional output of the previous layer into a one-dimensional vector. This is necessary because the output of convolutional and pooling layers is typically multi-dimensional, while the input to fully connected layers (also known as dense layers) is one-dimensional.

The Flatten layer simply takes the multi-dimensional input data and flattens it into a one-dimensional vector by stacking the rows of the input data on top of each other. This flattened vector can then be fed into a fully connected layer for further processing.

4.Dense Layer- A Dense layer, also known as a fully connected layer, is a type of layer used in neural networks where each neuron is connected to every neuron in the previous layer. In a convolutional neural network (CNN), Dense layers are typically used at the final stage of the network to perform classification.

Dense layers perform a linear operation where every output is formed by a function based on every input. The operation can be represented as output = activation(dot(input, kernel) + bias), where activation is the element-wise activation function, kernel is a weights matrix, and bias is a bias vector.

Dense layers can be used to learn complex relationships between the extracted features from the previous layers and the output classes.

In our model we have used 4 layers of Conv2D and MaxPooling2D alternatively followed by a flatten layer and lastly a Dense layer [3][6].

After adding the above mentioned layers finally model.summary() is called which is a method in Keras that can be used to print a summary of a CNN architecture. It provides a quick and easy way to visualize the structure of the model, including the number of layers, the output shape of each layer, and the number of parameters in each layer.

The summary includes information about the total number of parameters in the model, as well as the number of trainable and non-trainable parameters. This can be useful for understanding the complexity of the model and for debugging issues with the architecture.

Overall, model.summary() is a useful tool for understanding and visualizing the structure of a CNN architecture.

In our model we have used adam as the optimizer and loss as

SparseCategoricalCrossentropy , with accuracy as our metrics during compiling the model.

The below figure shows all the implementation of the above mentioned layers.

```
In [61]: input_shape = (BATCH_SIZE, IMAGE_SIZE, IMAGE_SIZE, CHANNELS)
         n_classes = 7

         model = models.Sequential([
             resize_and_rescale,
             layers.Conv2D(32, kernel_size = (3,3), activation='relu', input_shape=input_shape),
             layers.MaxPooling2D((2, 2)),
             layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
             layers.MaxPooling2D((2, 2)),
             layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
             layers.MaxPooling2D((2, 2)),
             layers.Conv2D(64, (3, 3), activation='relu'),
             layers.MaxPooling2D((2, 2)),
             layers.Flatten(),
             layers.Dense(64, activation='relu'),
             layers.Dense(64, activation='relu'),
             layers.Dense(n_classes, activation='softmax'),
         ])
         model.build(input_shape=input_shape)

In [62]: model.summary()
```

Fig 5.3 CNN Architecture

5.3 IMAGE RECOGNITION AND PROCESSING

5.3.1 OpenCV

OpenCV is an open-source computer vision and machine learning library used for image and video processing. It is written in C++ and can be used with Python, Java, and other programming languages. OpenCV provides a variety of functions for image processing, such as image filtering and image segmentation. In our project, we used OpenCV for image processing tasks such as image filtering and image segmentation.

5.4 USER INTERFACE

The user interface is designed to be simple and user-friendly. Users can drag and drop or upload an image of a face using the "Upload Image" button as shown in the figure 5.2.

After uploading the image , it is sent to the backend where FastAPI handles the request. The image is then processed by the model which predicts the expression in the image. This predicted expression is then sent back to the frontend where it is displayed using React and Material UI.

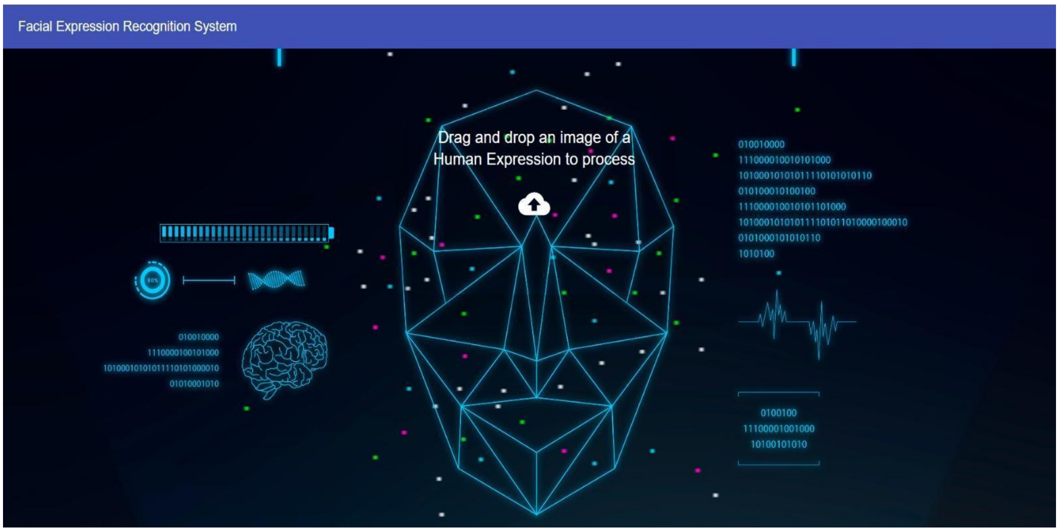


Fig 5.4 Landing Page

5.5 SAMPLE OUTPUTS

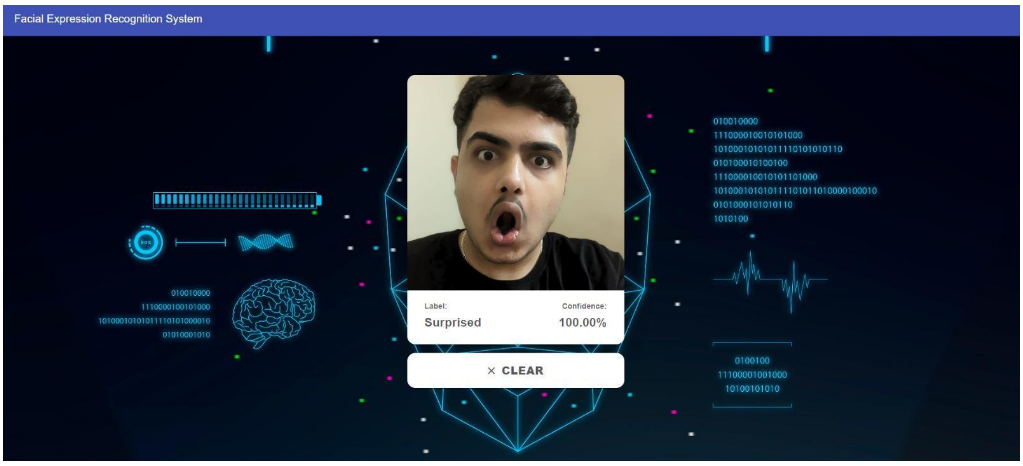


Fig 5.5 Surprised

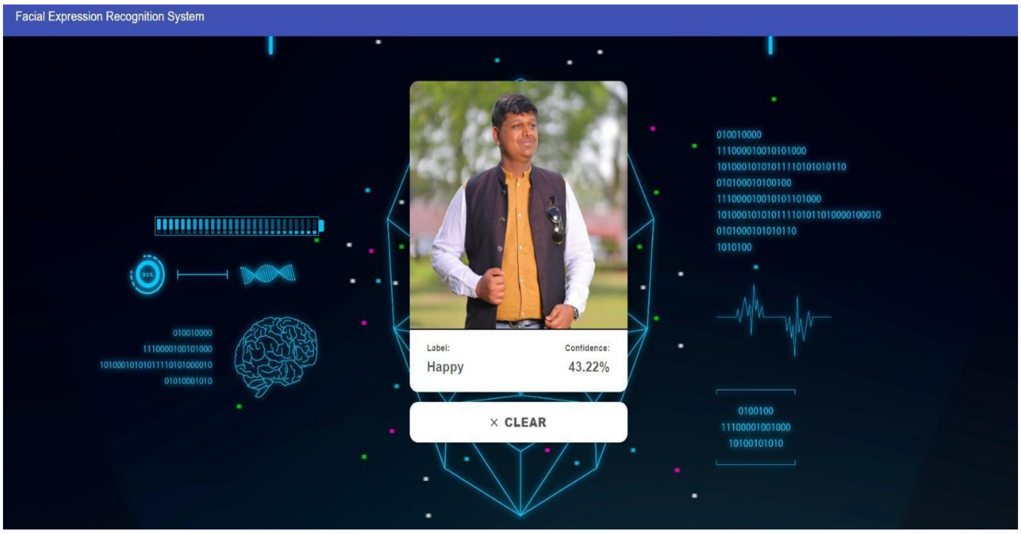


Fig 5.6 Happy

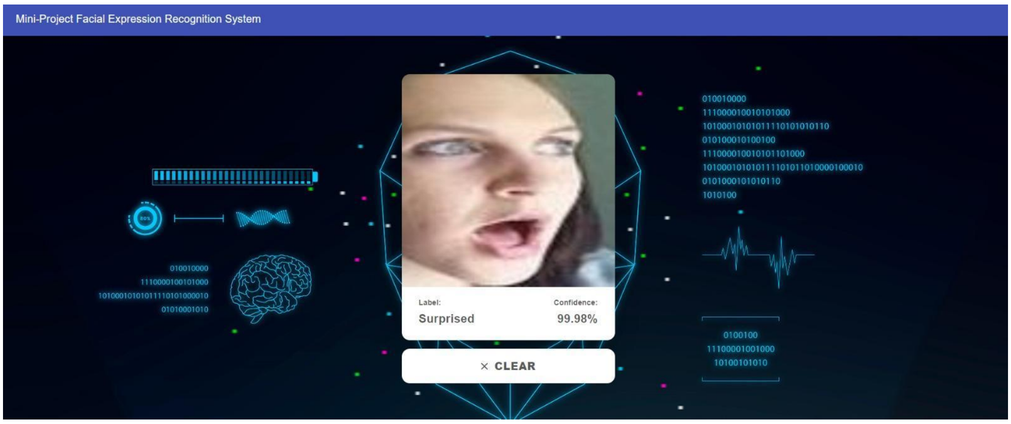


Fig 5.7 Surprised

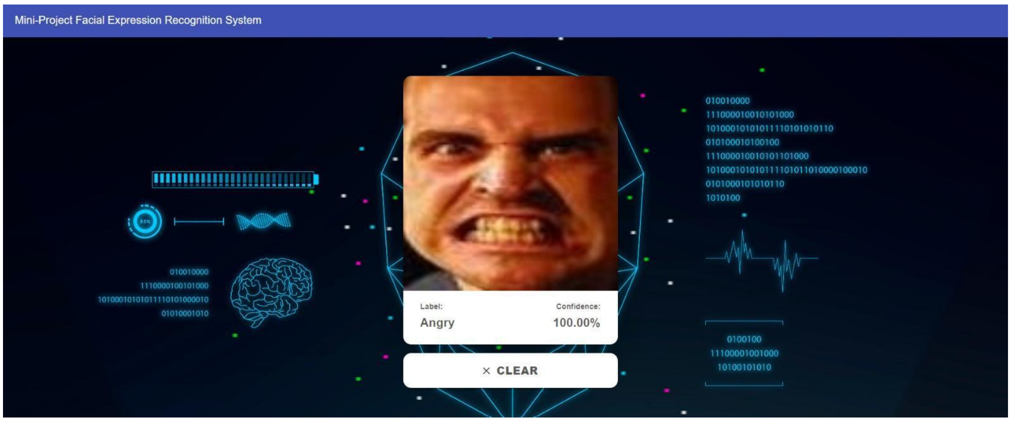


Fig 5.8 Angry

The Label shows the predicted facial expression by the model and the Confidence shows the prediction made by a model falls within a certain range of values, called the confidence interval.

CHAPTER 6

RESULT AND ANALYSIS

6.1-Results of different models after training them based on training and validation accuracy are as follows:

Training and validation Accuracy on FER dataset

```
Epoch 47/50
574/574 [==============================] - 43s 75ms/step - loss: 0.2127 - accuracy: 0.9254 - val_loss: 0.9216 - val_accuracy:
0.8496
Epoch 48/50
574/574 [==============================] - 40s 70ms/step - loss: 0.2203 - accuracy: 0.9220 - val_loss: 0.9954 - val_accuracy:
0.8250
Epoch 49/50
574/574 [==============================] - 40s 70ms/step - loss: 0.2043 - accuracy: 0.9273 - val_loss: 0.8506 - val_accuracy:
0.8641
Epoch 50/50
574/574 [==============================] - 43s 75ms/step - loss: 0.1852 - accuracy: 0.9317 - val_loss: 0.8848 - val_accuracy:
0.8599
```

Fig 6.1

Prediction On FER Dataset

Fig 6.2

Training and validation Accuracy on Transfer Learning model Using MobileNetV2

```
Epoch 20/25
397/397 [==============================] - 663s 2s/step - loss: 0.2394 - accuracy: 0.9157
Epoch 21/25
397/397 [==============================] - 661s 2s/step - loss: 0.2124 - accuracy: 0.9282
Epoch 22/25
397/397 [==============================] - 664s 2s/step - loss: 0.2240 - accuracy: 0.9218
Epoch 23/25
397/397 [==============================] - 663s 2s/step - loss: 0.2001 - accuracy: 0.9301
Epoch 24/25
397/397 [==============================] - 665s 2s/step - loss: 0.1856 - accuracy: 0.9379
Epoch 25/25
397/397 [==============================] - 666s 2s/step - loss: 0.1735 - accuracy: 0.9380

Out[47]: <keras.callbacks.History at 0x2a1c8db9910>
```

Fig 6.3

Layer Used in Transfer learning Model

```
In [34]:  1 model = tf.keras.applications.MobileNetV2() ## Pre-trained model

In [35]:  1 model.summary()

Model: "mobilenetv2_1.00_224"
_________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
=================================================================================================
 input_1 (InputLayer)           [(None, 224, 224, 3  0           []
                                )]

 Conv1 (Conv2D)                 (None, 112, 112, 32  864         ['input_1[0][0]']
                                )

 bn_Conv1 (BatchNormalization)  (None, 112, 112, 32  128         ['Conv1[0][0]']
                                )

 Conv1_relu (ReLU)              (None, 112, 112, 32  0           ['bn_Conv1[0][0]']
                                )

 expanded_conv_depthwise (Depth  (None, 112, 112, 32  288        ['Conv1_relu[0][0]']
 wiseConv2D)                    )
```

Fig 6.4

Training and validation Accuracy RAF dataset 48X48.

```
In [31]: history = model.fit(
             train_ds,
             batch_size=BATCH_SIZE,
             validation_data=val_ds,
             verbose=1,
             epochs=50,
         )

0.9245
Epoch 45/50
384/384 [==============================] - 20s 52ms/step - loss: 0.0596 - accuracy: 0.9798 - val_loss: 0.4974 - val_accuracy:
0.9258
Epoch 46/50
384/384 [==============================] - 32s 83ms/step - loss: 0.0797 - accuracy: 0.9729 - val_loss: 0.5086 - val_accuracy:
0.9134
Epoch 47/50
384/384 [==============================] - 24s 61ms/step - loss: 0.0742 - accuracy: 0.9738 - val_loss: 0.5154 - val_accuracy:
0.9108
Epoch 48/50
384/384 [==============================] - 20s 51ms/step - loss: 0.0452 - accuracy: 0.9841 - val_loss: 0.5604 - val_accuracy:
0.9193
Epoch 49/50
384/384 [==============================] - 33s 85ms/step - loss: 0.0864 - accuracy: 0.9680 - val_loss: 0.5441 - val_accuracy:
0.9043
Epoch 50/50
384/384 [==============================] - 22s 57ms/step - loss: 0.0813 - accuracy: 0.9722 - val_loss: 0.5400 - val_accuracy:
0.9147
```

Fig 6.5

Prediction ON RAF dataset 48X48.

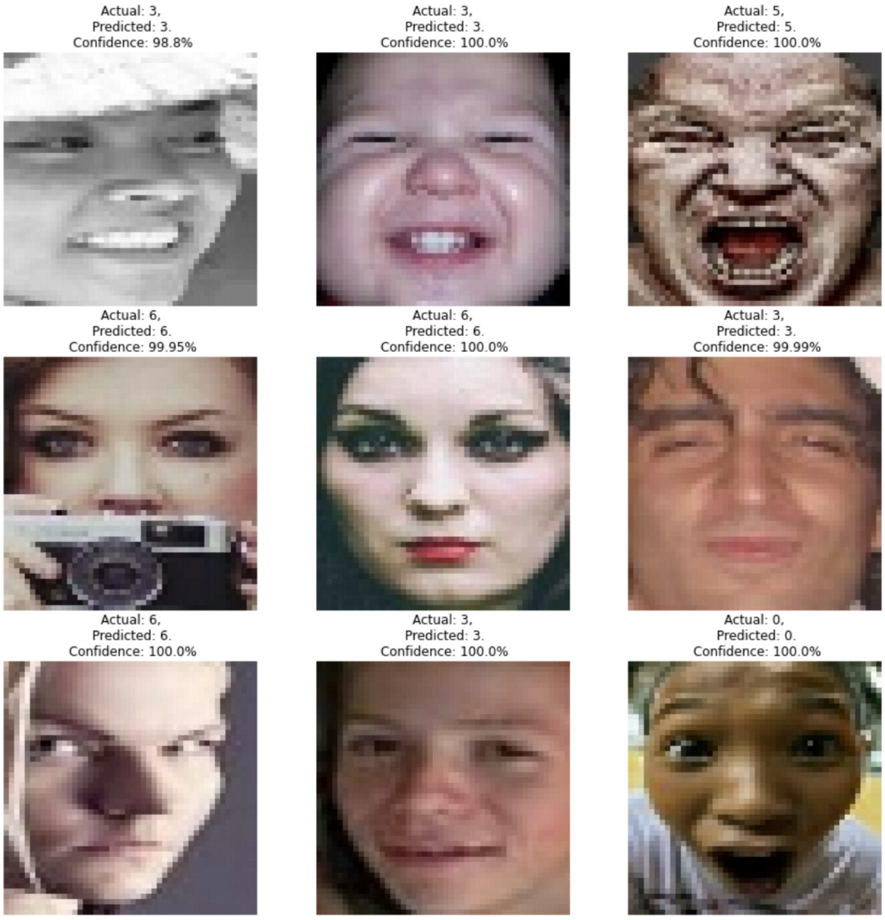


Fig 6.6

Training and validation Accuracy RAF + FER dataset 48X48.

```
y: 0.8677
Epoch 45/50
656/656 [==============================] - 52s 79ms/step - loss: 0.2367 - accuracy: 0.9124 - val_loss: 0.6687 - val_accurac
y: 0.8534
Epoch 46/50
656/656 [==============================] - 47s 72ms/step - loss: 0.2430 - accuracy: 0.9101 - val_loss: 0.6984 - val_accurac
y: 0.8490
Epoch 47/50
656/656 [==============================] - 47s 72ms/step - loss: 0.2259 - accuracy: 0.9182 - val_loss: 0.6225 - val_accurac
y: 0.8628
Epoch 48/50
656/656 [==============================] - 49s 74ms/step - loss: 0.2175 - accuracy: 0.9223 - val_loss: 0.6784 - val_accurac
y: 0.8532
Epoch 49/50
656/656 [==============================] - 49s 75ms/step - loss: 0.2247 - accuracy: 0.9187 - val_loss: 0.6389 - val_accurac
y: 0.8699
Epoch 50/50
656/656 [==============================] - 52s 79ms/step - loss: 0.1896 - accuracy: 0.9314 - val_loss: 0.7323 - val_accurac
y: 0.8571
```

Fig 6.7

Prediction ON RAF + FER dataset 48X48.

Fig 6.8

Training Accuracy and Validation accuracy on RAF 100 X 100 .

```
384/384 [==============================] - 117s 304ms/step - loss: 0.0753 - accuracy: 0.9761 - val_loss: 0.5445 - val_accuracy:
0.9258
Epoch 46/50
384/384 [==============================] - 96s 249ms/step - loss: 0.0501 - accuracy: 0.9835 - val_loss: 0.6539 - val_accuracy:
0.9134
Epoch 47/50
384/384 [==============================] - 93s 242ms/step - loss: 0.0634 - accuracy: 0.9791 - val_loss: 0.5876 - val_accuracy:
0.9212
Epoch 48/50
384/384 [==============================] - 93s 242ms/step - loss: 0.0611 - accuracy: 0.9796 - val_loss: 0.6276 - val_accuracy:
0.9121
Epoch 49/50
384/384 [==============================] - 93s 242ms/step - loss: 0.0650 - accuracy: 0.9782 - val_loss: 0.6073 - val_accuracy:
0.9284
Epoch 50/50
384/384 [==============================] - 95s 246ms/step - loss: 0.0594 - accuracy: 0.9799 - val_loss: 0.6165 - val_accuracy:
0.9264
```

Fig 6.9

Testing Accuracy on RAF 100 X 100 .

```
1/1 [==============================] - 0s 71ms/step
1/1 [==============================] - 0s 59ms/step
1/1 [==============================] - 0s 74ms/step
1/1 [==============================] - 0s 73ms/step
1/1 [==============================] - 0s 67ms/step
1/1 [==============================] - 0s 71ms/step
1/1 [==============================] - 0s 65ms/step
1/1 [==============================] - 0s 72ms/step
1/1 [==============================] - 0s 62ms/step
1/1 [==============================] - 0s 63ms/step
1/1 [==============================] - 0s 64ms/step
1/1 [==============================] - 0s 57ms/step
1/1 [==============================] - 0s 69ms/step
1/1 [==============================] - 0s 62ms/step
Total testing images => 1536
Testing Accuracy of our model is => 0.935546875

<Figure size 1080x1080 with 0 Axes>
```

Fig 6.10

Prediction On RAF 100 X 100 .

Fig 6.11

NAMES	Data set	image Size	#images	#images - training	#images - testing	Batch Size	Epochs	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
Con1	FER-13	48x48	28709	80% of images	10% of images	32	50	0.9271	0.2072	0.8497	0.7463
Con2	FER-13	48x48	28709	80% of images	10% of images	40	50	0.9317	0.1852	0.8599	0.8848
Con3	RAF	48x48	5170	80% of images	10% of images	32	50	0.9713	0.0805	0.9141	0.6611
Con4	RAF	48x48	15339	80% of images	10% of images	32	50	0.9722	0.0813	0.9147	0.54
Con5	RAF	100x100	15339	80% of images	10% of images	32	50	0.98	0.0594	0.9264	0.6165
Con6	RAF+FER	48x48	41000	80% of images	10% of images	32	50	0.9314	0.1896	0.8571	0.7323

Table 6.1

A Confusion Matrix is drawn for the same model(Con5) below:

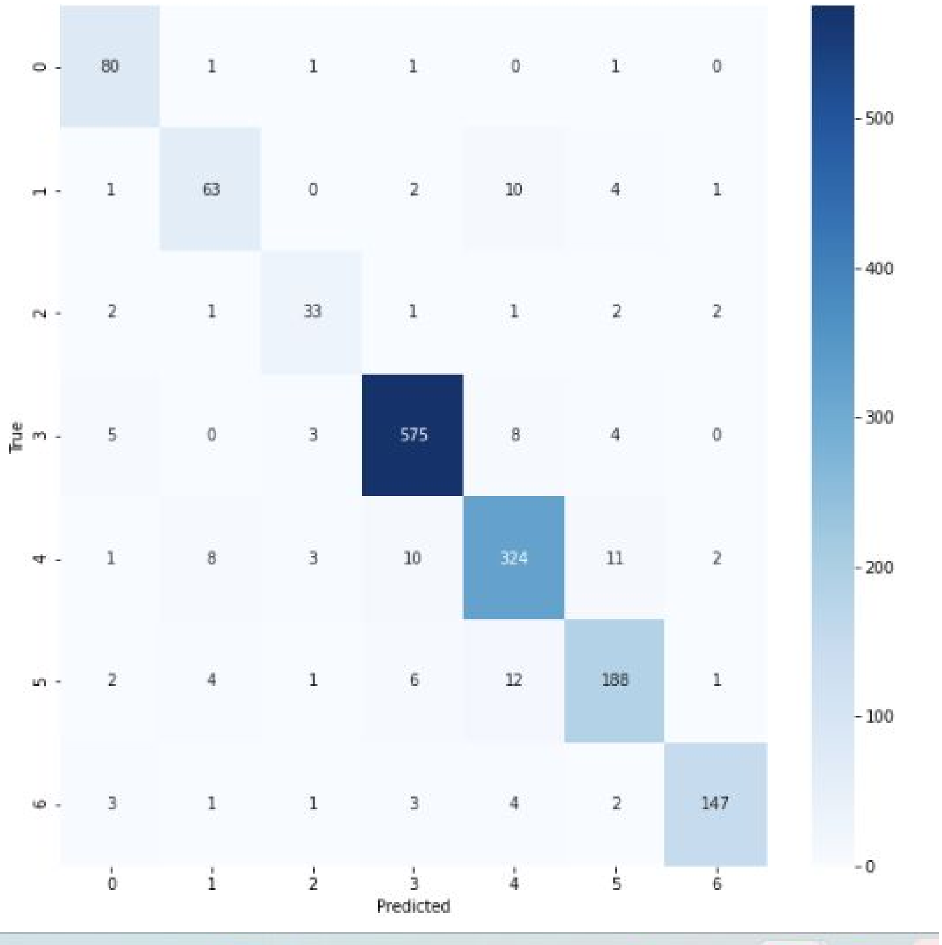


Table 6.2

Based on our analysis of different models for facial expression recognition, we have determined that the most effective model is the one trained using the RAF dataset with an image size of 100x100x3 pixels. The RAF dataset is a large collection of facial expression images that we used to train Conv5 model. By using an image size of 100x100x3, we were able to provide Con5 with a high level of detail in the training images, which likely contributed to its strong performance.

In addition to using the RAF dataset and an image size of 100x100x3 pixels, we also trained it using a CNN architecture shown in Fig 5.3. CNNs, or convolutional neural networks, are a type of neural network architecture that is particularly well-suited for image classification tasks. By using a CNN architecture shown in Fig 5.3, we were able to effectively train Con5 model to recognize and classify different facial expressions.

Overall, the Con5 model achieved a high training accuracy of 0.98 and a testing accuracy of 0.935. This indicates that the model performed very well on both the data it was trained on and on new data that it had not seen before. These results suggest that Con5 model is highly effective at detecting facial expressions.

In addition to the details mentioned earlier, it is also important to note that we designed our own layers for the CNN architecture used in our facial expression recognition model shown in Fig 5.3.Despite this, it still achieved a high level of performance. This demonstrates the effectiveness of Con5 model design and training approach.

6.2 METRICS FOR COMPARISON

In the process of developing a machine learning model for facial expression recognition, we used two metrics to evaluate the performance of different models: training accuracy and testing accuracy. Training accuracy measures how well a model performs on the data it was trained on. Testing accuracy measures how well a model performs on a dataset that it has not seen before. By comparing the training and testing accuracy of different models, we were able to determine which models were most effective at detecting facial expressions.

Based on our analysis, we have determined that the most effective model for facial expression recognition is the one trained using the RAF dataset with an image size of 100x100x3 pixels which is Con5 model. This model, which was trained on nearly 15,000 images using a CNN architecture, achieved a high training accuracy of 0.98 and a testing accuracy of 0.935, indicating strong performance in both training and testing scenarios.

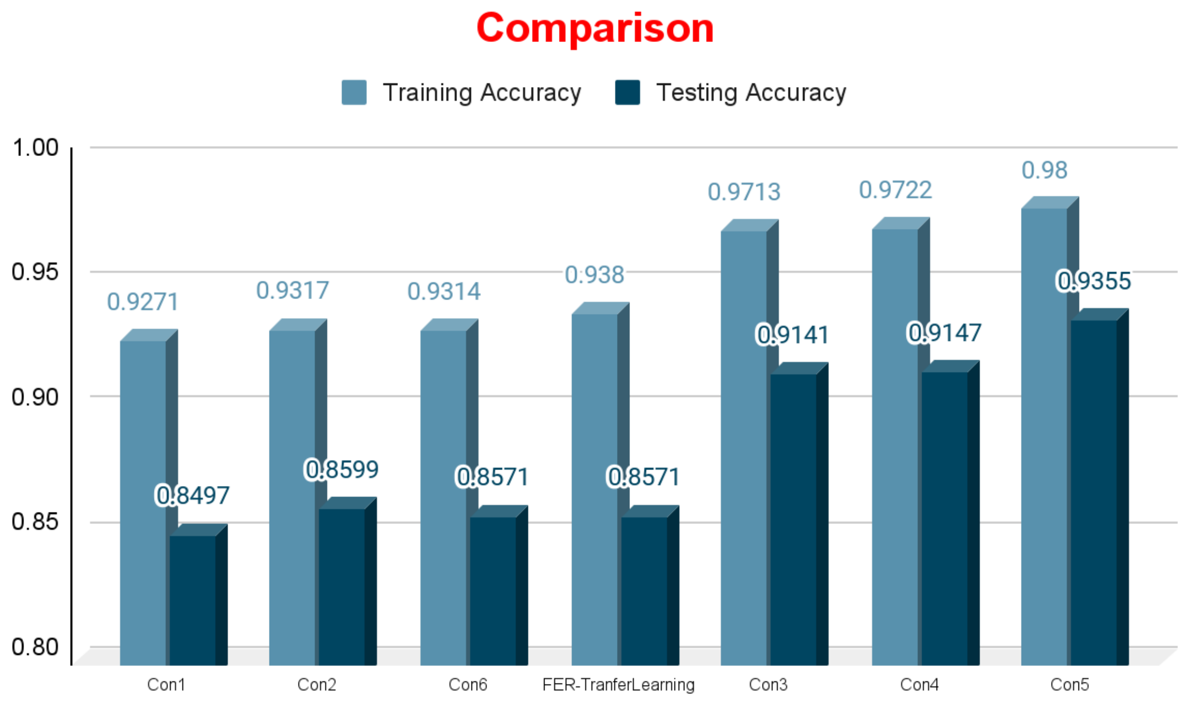


Fig 6.12

CHAPTER 7

DISCUSSION

7.1 Societal Impacts:

The development of an accurate facial expression recognition system carries significant societal impacts. In the context of human-computer interaction, this technology can revolutionize the way we interact with computers, robots, and virtual assistants. It opens up possibilities for more natural and intuitive user interfaces, enabling devices to understand and respond to human emotions effectively. This can enhance user experiences and improve the overall usability of technology in various domains, such as education, healthcare, and entertainment.

Moreover, in the field of emotion analysis and mental health assessment, facial expression recognition can provide valuable insights into emotional states, aiding psychologists and researchers in understanding and diagnosing mental health conditions. This technology has the potential to contribute to the early detection and treatment of mental health disorders, improving overall well-being and quality of life for individuals.

However, it is crucial to consider the ethical implications associated with facial expression recognition. Privacy concerns arise when facial data is collected and processed, raising questions about consent, data security, and potential misuse of personal information. Safeguards and regulations must be implemented to ensure the responsible and ethical use of facial expression recognition technology to protect individuals' privacy and prevent discriminatory practices.

7.2 Ethical and Sustainability Considerations:

The ethical implications of facial expression recognition encompass various aspects. Firstly, transparency and explainability of the system's decision-making process are crucial. Users and stakeholders should have a clear understanding of how the system works, what data is being collected, and how the facial expressions are being interpreted. This transparency fosters trust and accountability in the technology.

Additionally, biases in facial expression recognition algorithms need to be addressed. The potential for biased predictions or misclassifications based on factors such as race, gender, or cultural differences can lead to unfair treatment or discrimination. Continuous evaluation and mitigation of biases should be carried out throughout the development and deployment of facial expression recognition systems to ensure fairness and avoid reinforcing existing societal prejudices.

From a sustainability perspective, the computational resources required for training and deploying facial expression recognition models should be considered. Energy consumption and carbon footprints associated with running these models should be minimized. Optimization techniques, model compression, and efficient hardware implementations can contribute to sustainable deployment of the technology.

7.3 Future Work:

Future research and development in facial expression recognition can focus on several areas. Firstly, improving the system's performance on specific expressions that might be more challenging to recognize accurately, such as subtle or culturally influenced expressions. Collecting more diverse and balanced datasets can help address this issue[1][2][5].

Furthermore, real-time implementation of facial expression recognition systems can enhance their usability and practicality in various applications. Optimizing the models and leveraging hardware accelerators can enable faster and more efficient recognition, facilitating real-time feedback and interaction[4].

In terms of ethical considerations, ongoing efforts should be made to address biases and ensure fairness in the recognition of facial expressions. This involves collecting representative datasets, developing bias detection mechanisms, and implementing fairness-aware algorithms to minimize disparities and avoid discriminatory outcomes.

CHAPTER 8

CONCLUSION

In conclusion, this project on facial expression recognition has successfully achieved its objectives of designing and implementing an accurate and efficient system for recognizing and classifying facial expressions. The project utilized machine learning techniques, including data collection, preprocessing, feature extraction, model training, and evaluation.

Through the careful compilation of a diverse dataset and the application of preprocessing techniques, the system was able to handle various facial expressions and ensure the consistency and quality of the data. The extraction of relevant features, including geometric and appearance-based features, allowed the system to capture essential information from the facial images.

The implementation and comparison of different machine learning algorithms demonstrated the superiority of convolutional neural networks (CNNs) in learning complex features and capturing spatial dependencies within the facial images. The CNN-based model exhibited robust performance, achieving high accuracy in recognizing and classifying facial expressions.

However, it is important to acknowledge the limitations and challenges encountered during the project. Dataset bias, limited computational resources, and potential biases in recognizing certain expressions were identified as areas for improvement. To address these limitations, future research could explore data augmentation techniques and incorporate domain-specific knowledge to enhance the system's performance.

The findings of this project have significant implications for various fields, including human-computer interaction, emotion analysis, and mental health assessment. The accurate recognition of facial expressions can enable more natural and intuitive human-computer interfaces, provide valuable insights into emotional states for psychological research, and assist in mental health diagnosis and treatment.

In summary, this facial expression recognition project has made valuable contributions to the field by developing an accurate and efficient system capable of recognizing and classifying facial expressions. The project outcomes pave the way for further advancements in facial expression recognition technology, and future research can build upon this foundation to improve performance on specific expressions and explore real-time implementation possibilities.

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