VISVESVARAYA TECHNOLOGICAL UNIVERSITY
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Mini Project Report on

"A COMPARATIVE STUDY OF TRADITIONAL MACHINE LEARNING AND DEEP LEARNING FOR EMOTION RECOGNITION"

Submitted in partial fulfilment for the award of degree of

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in

ELECTRONICS & COMMUNICATION ENGINEERING

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CERTIFICATE

This is to certify that Mini Project work entitled **"A Comparative Study of Traditional Machine Learning and Deep Learning for Emotion Recognition"** carried out by **Deepthi Kashyap M K(4SF22EC027),Hemnath Kumar H N(4SF22EC042), Mahesh(4SF22EC056), Sneha(4SF22EC107)** who are the bonafide students of Department of Electronics & Communication Engineering, Sahyadri College of Engineering & Management, Mangaluru in partial fulfillment for the award of Bachelor of Engineering in Electronics & Communication Engineering of the Visvesvaraya Technological University, Belagavi, during the academic year 2024-2025. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the Departmental library. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the Bachelor of Engineering Degree.

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DECLARATION

We hereby declare that the entire work embodied in this Mini Project titled **"A Comparative Study of Traditional Machine Learning and Deep Learning for Emotion Recognition"** has been carried out by us at Sahyadri College of Engineering & Management, Mangaluru under the supervision of **Prof. Roopashree** for **Bachelor of Engineering** in **Electronics & Communication Engineering**. This report has not been submitted to this or any other University for the award of any other degree.

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ABSTRACT

Facial emotion recognition have become the fundamental component of the modern artificial intelligence applications. This study approaches to the study of the comparison to the traditional methods including Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), Oriented FAST and Rotated BRIEF (ORB), and Histogram of Oriented Gradient (HOG) and the deep learning methods specifically, Convolution Neural Networks (CNNs). This system is trained on the FER (2013) dataset having the six different class including anger, disgust, sadnesses, happiness and fear. By comparing to the traditional and the deep learning approaches, we delve to work on the machine learning approach as it gives more accuracy, reliability and scalability. The findings underscore the transformation potential of the CNNs in detecting the facial emotions.

Our initiative focuses on the facial emotion detection by capturing the images and with the added capability of real-time analysis. It paves the way for the mental health monitoring, human-computer interaction and the customer experience enhancement.

By integrating and detecting through different approaches we have come to the best approach which provides to robust and the nuanced understanding of the emotions.

This analysis provides the meaningful insights of facial emotion recognition techniques, and emphasizing the potential of the CNN across mental health and the stress management by providing the accurate emotion recognition features.

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List of Abbreviations

Abbreviations	Full Form
FER	Facial Emotion Recognition
LBP	Local Binary Patterns
SIFT	Scale-Invariant Feature Transform
ORB	Oriented FAST and Rotated BRIEF
HOG	Histogram of Oriented Gradients
CNN	Convolutional Neural Networks
FAST	Features From Accelerated Segment Test
BRIEF	Binary Robust Independent Elementary Features
EEG	Electroencephalography
JAFFE	Japanese Female Facial Expression
CK+	Extended Cohn-Kanade
MSIFT	Modified Scale-Invariant Feature Transform
RAFDB	Real-world Affective Faces Database
SACNN	Spatial Attention Convolutional Neural Network
LSTM	Long Short-term Memory network
ALSTMs	Attention Long Short-term Memory
MTCNN	Multi-Task Cascaded Convolutional Neural Network
SDM	Supervised Descent Method
SVM	Support Vector Machine
STED	Situ Emotion Dataset
MBCC-CNN	Multiple Branch Cross Connected-CNN
RAF	Real-world Affective Faces
XG Boost	Extreme Gradient Boosting
ESRs	Ensembles with Shared Representations
MMI	Multi-Modal Interaction
ROI	Region of Interest
KDEF	Karolinska Directed Emotional Faces
YCBCR	Luminance, Chrominance (Blue), Chrominance (Red)
VGG-16	Visual Geometry Group 16
UMD	Upper and Middle-level Descriptors
DSAE	Deep Stacked Autoencoders

Organization of Thesis

This report is organized into the following chapters,

Chapter 1: Introduction

This chapter presented the project topic, including Background of the study, Problem statement, Objective, Scope of the work, and Motivation of the project.

Chapter 2: Literature Survey

In this chapter, appropriate literature related to topic is analysed. It emphasizes theories, model, and previous research that form a framework for our study, and determines the gaps.

Chapter 3: Methodology

This chapter describes the methodology used to build a project. This includes data collection, data preprocessing, feature extraction, model training, and model evaluation.

Chapter 4: System Design

This chapter contains classification models, Contrast used for designing a project.

Chapter 5: Results and Discussions

The result of this project is presented in this chapter. This chapter consists of model performance evaluation, comparison with other models, insights and future work.

Chapter 6: Conclusions

This chapter summarizes the project, key finding, and future work.

References:

A list of all the sources and references cited throughout the project is included in this section.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

The ability to recognize human emotions is essential for understanding non-verbal communications. They have wide range of applications from mental health monitoring to customer experience enhancement. Recognition of facial emotions have become a critical focus in the fields of Artificial Intelligence, human-computer interactions and psychology. Identifying the mental health stress at an early stage is crucial, as it prevents multitude of health issues related to stress and maintaining overall health and balance. Machine learning and the Deep learning have brought the vast changes, they enable things like predicting diseases earlier, making personalized recommendations online and providing safety. Detecting facial emotions is a cutting-edge application of Machine learning and the Deep learning. The emotion recognition requires a higher level of knowledge. Facial Emotion Recognition (FER) is related to the systems that aims to analyze the facial movements and facial feature changes to recognize a facial expression. The FER is different from the emotion recognition. The emotion recognition require high level of knowledge despite the facial expression could indicate an emotion. The FER (2013) dataset included the six basic classes of emotions: anger, disgust, fear, happiness, sadness, and surprise. This approach involves the gathering of the traditional methods and the Deep learning methods for the facial emotion recognition. Traditional methods have relied on the feature extraction such as, Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), Oriented FAST and Rotated BRIEF(ORB), and Histogram of Oriented Gradients (HOG). Looking into the overview of each traditional models,

1. Local Binary Patterns (LBP): It is widely used in the image analyses and pattern recognition. It is worked by dividing images to the small regions. LBP works well for grayscale images and robust to monotonic illumination changes. The texture of the image is specified in LBP by plotting the histograms by the binary patterns. It is limited in capturing the global features of the image.

2.Scale-Invariant Feature Transform (SIFT): These mainly describes the local features of the images. SIFT is effective in identifying features under the various lighting conditions. It identifies edges and corners. These are computationally expensive comparing to the similar methods to the LBP.

3.Oriented FAST and Rotated BRIEF (ORB): These are the efficient alternative to the SIFT and SURF**,** designed for the real time applications. It combines the FAST (Features from Accelerated Segment Test) key-point detectors with the BRIEF (Binary Robust Independent Elementary Features) descriptors. It is suitable for the real time systems. In ORB limited accuracy in the textured images.

4.Histogram of Oriented Gradients (HOG): It is a feature description that analyses the portion of gradient directions. HOG divides images into small cells and computes histograms. In detecting shapes and edges in images HOG is very effective. The complexity is heavier than that of the LBP.

1.2 Problem Statement

These are the traditional methods used to detect the facial emotion. While these traditional methods have been the foundational in facial emotion recognition, they often struggle with variability in lighting, pose, and occlusions, and thus paving the way for deep learning approaches like Convolutional Neural Networks (CNNs). In contrast, Convolution Neural Networks (CNNs) a Deep learning based approach have revolutionized feature extraction and classification in emotion recognition. CNNs excel at detecting patterns, enabling to achieve remarkable accuracy and reliability. Their ability to process large dataset allows CNNs to generalize well across the diverse populations. Real time analysis is the advanced application that processes the live video stream to detect and classify the facial emotions. Despite the challenges faced like the lighting variations, pose differences these system excel in recognition of facial emotion detection.

In this approach we have done the comparison of the Traditional methods of emotion recognition and the Deep learning methods of the facial emotion recognition. By study of the strengths, accuracy and the efficiency of the models of the traditional approaches, we claim that the Deep learning approach is more preferred choice. It provides the most reliable, accurate and scalable solution for the real time emotion recognition. Through this study, its not only advantageous of the technology of the deep learning but also the potential for the mental health monitoring through the deep learning approaches. The insights gained from this comparison will be advantageous for the real time emotion recognition. This holds immense promise for stress monitoring and mental health support, potentially accessing means of understanding.

1.3 Objectives

Comparison of traditional methods to detect the facial emotion and the deep learning approaches specifically the CNNs, have some key objectives,

- Exploring and evaluating the Traditional facial recognition method.
- Deep Learning methods specifically Convolution Neural Networks (CNNs).
- Comparing the performance and the accuracy of both Traditional and the Deep learning methods.

1.4 Scope of the Work

Advancements in Technology: Integrating physiological indicators such as (heart rate and EEG) with speech text to provide the comprehensive comprehension of emotions.

Optimizing Edge Devices: Real-time emotion detection on embedded systems and cell-phones. creation of CNN architectures that are lightweight and energy-efficient (such as Mobile Net and Res-Net) in order to balance computational efficiency and accuracy.

Domain – Specific Applications: In Mental Health, Detecting stress, anxiety, or early signs of depression. Personalized therapeutic interventions based on real-time emotional states. In Education, tracking students emotional involvement in virtual or online learning environments in real time.

Ethical Considerations: putting privacy-preserving strategies into practice, such as federated learning, to guarantee data confidentiality, preventing illegal access or exploitation of user data.

Future Research Opportunities: Combining models that are hybrid, integrating deep learning with rule-based systems to improve performance and interpretability.

1.5 Motivation of the Report

The motivation for this project is propelled by the increasing importance of facial emotion recognition (FER) in AI applications like human-computer interaction, customer experience improvement, and mental health monitoring. The widely used machine learning algorithms are ORB, LBP, SIFT, and HOG sometimes struggle with complicated patterns and scalability. Deep learning methods, in particular Convolutional Neural Networks (CNNs), provide more accuracy, robustness, and dependability. In order to improve stress management, mental health treatment, and adaptive systems, this study compares these traditional and deep learning algorithms with an focus on their real-time emotion detection capabilities. The final objective is to determine the best method for real-time emotion recognition in order to elevate innovation in AI applications.

CHAPTER 2

LITERATURE SURVEY

D Hema et al. [1] their work has recognized about the Patch-SIFT, collects features from the multiple patches within the images. The extracted features are trained and tested on the ensemble model. The improved version of SIFT, Patch-SIFT is applied for the facial emotion recognition and done using JAFFE and CK+ dataset. The authors have emphasized the classification process accomplished by using a customized ensemble classifier.

Vitoria et al. [2] propose the facial emotion recognition. The methodology proposes based on parameterized photograms and machine learning techniques. In this two strategies were employed: first, emotional photograms were collected and categorized. Second, these trained classifiers were applied to classify the emotions. Their work carried out the different classifier combination methods in facial emotion recognition.

Mundher et al. [3] the paper initiates towards the Facial Emotion Recognition task. The proposed method is based on the Convolution Neural Networks (CNN) on the face recognition problem. Scale- Invariant Feature Transform (SIFT) are used to increase the performance on the small data. Both Dense SIFT and SIFT are studied and compared when merged with CNN features. The results are more accurate with CNN with Dense SIFT than the CNN with SIFT.

Nirvair et al. [4] introduces an efficient work to fully develop automatic face recognition algorithm. In this paper Modified SIFT (MSIFT) has been proposed to enhance the recognition performance using SIFT. The work here is done in three steps. First, smoothing of the images have been done. Second, computational complexity of SIFT. Third, the algorithm is made automatic. The main aim of this project is to reduce to database size, the experiments are performed on the JAFFE database. It shows robustness against various facial expressions.

Chieh-Ming et al. [5] suggests that in their work a compact framework based facial expression recognition is achieved. They introduced a new Convolution Neural Networks (CNN) for improving the performance of deep networks. They developed an illumination augmentation scheme to improve the robustness of training the proposed CNN model. In this paper they have compared the work of training with illumination augmentation and direct training and have come to the conclusion that, training with the illumination augmentation have the more accurate accuracy than the direct training.

Ali et al. [6] proposed a Automatic Facial Expression Recognition using Ad-Corre. It consists of three components called Feature Discriminator, Mean Discriminator ,and Embedding Discriminator using CNN. The methodology involves utilizing of correlation matrix for Examine the homogeneity between each pair within a mini batch. The model has achieved greater accuracy on Affect Net and RAFDB, FER2013.

Chang et al. [7] contribute to the Facial Emotion Recognition with their titled "Facial Expression Recognition using Hybrid Features of Pixel and Geometry. The method involves Spatial Attention Convolutional Neural Network (SACNN) to excavate the pixel level features and a Long Short term Memory network (LSTM) with Attention mechanism (ALSTMs) to comprehend the geometric position. The system uses datasets from FER2013, CK+, and JAFFE to analyse the performance of the system.

Tanoy et al. [8] they proposed a facial emotion recognition model that combines LBP (Local using a convolution neural network and the model using ORB (Oriented fast and rotated brief) with facial expressions obtained from LBP(Local Binary Patterns), and used CNN (Convolution Neural Network) for detecting seven emotions such as Fear, Happy, Sad, Angry, Disgust, Neutral and done using FER2013 databases and then CK+ dataset . They proposed three steps for emotion recognition mechanism. First, is to prepare the dataset. Second, is to identify the face obtained from images during feature extraction. Third, to divide images into seven emotions And achieved validation accuracy of 91.01%.

Chahak et al. [9] contribute to facial emotion recognition model using Handcrafted features and CNN. The methodology sourced the dataset from CK+ and JAFFE and model is based on Convolution Neural Network. The Histogram of Oriented Gradients (HOG) is employed for extraction of features from data and Scale Invariant Feature Transform (SIFT) for identifying local features of data. Both HOG-CNN and SIFT-CNN ensures greater accuracy with CK+ and JAFFE datasets.

Change et al. [10] implemented a hybrid Multi-feature Based Emotion Recognition for Video Clips. In this paper, MTCNN and SDM are utilized for face tracking and feature extraction is done from every image by mean, mode and standard deviation. The model is trained by SVM with the Image Dataset and Situ Emotion Dataset (STED). The Landmark Euclidean Distance (LMED) is utilized to calculate Euclidean Distance as a facial attributes. The addition Audio and LSTM results significantly improved the accuracy.

Cuiping et al. [11] this paper presented a new method for facial expressions recognition based on multiple branch cross connected convolutional neutral network (MBCC-CNN). The methodology involved collection of preprocessed images followed by image feature extraction and image recognition. The two methods for depicting face images. First, geometric feature based method. Second, texture feature based method with the dataset from CK+, FER+ and RAF. This paper is organized into three modules on the basis of residual connection, Network in Network, and tree structure. And the system is capable of detecting facial expressions rapidly and accurately.

B. Meena et al. [12] developed a hybrid model that blends Histogram of Oriented Gradients (HOG) for detecting faces with machine learning techniques like Random Forest and XG Boost for classification. Their approach achieved an impressive 95% accuracy, effectively tackling challenges like background noise and unbalanced datasets. This makes it a practical solution for crime detection scenarios.

Zhong et al. [13] introduced a novel technique called HOG-ESRs, which combines HOG features with Ensembles with Shared Representations (ESRs). This hybrid model minimizes generalization errors and enhances robustness. Their tests on the FER2013 dataset showed an accuracy of 89.3%, outperforming traditional methods and proving its effectiveness for real-world applications.

Saeed et al. [14] proposed a framework for facial expression recognition (FER) that utilizes HOG features with Random Forest classification. They addressed complex challenges like diverse facial expressions and incomplete face detection in uncontrolled environments. Evaluated on the JAFFE dataset, their approach achieved an average accuracy of 92.97%, effectively recognizing multiple expressions.

Niu et al. [15] developed a method for facial expression recognition that combines Local Binary Patterns (LBP) with an improved Oriented FAST and Rotated BRIEF (ORB) technique to extract meaningful features. Using Support Vector Machines (SVMs) for classification, their approach achieved impressive results on datasets like JAFFE, CK+, and MMI. The method is not only accurate but also efficient, making it practical for applications with limited hardware resources.

Mukta et al. [16] demonstrated a facial emotion recognition method that combines texture characteristics and key points descriptors. There are three stages to the process. ROI Extraction comes first. Feature Vector Fusion comes in second. Classification comes in third. Three datasets—JAFFE, CK+, and MMI—are used to assess the suggested methodology. The model helps create new fusion and eye centre algorithms.

Julina et al. [17] showed how two different methods HOG and LBP could help computers recognize emotions. Using HOG, their system correctly identified emotions 87% of the time, while LBP managed a respectable 64%. The technology has found applications across various domains including stress detection, customer behaviour analysis, e-learning systems, and mental health monitoring.

Erlangga et al. [18] contribute to imaged based facial emotion recognition using convolutional neural network. The methodology involves two CNN methods : transfer learning using fine-tuned MobileNet-V2 and Inception-V3 models, and a full learning approach with custom architectures streamlined through the Taguchi method. Data preprocessing encompasses video-to-frame conversion, face cropping, data cleaning, rearranging, splitting , rescaling, resizing and augmentation. Experimental results illuminate excellent performance and achieved greater accuracy , demonstrating the efficacy of advanced architectures and robust preprocessing for FER tasks.

Al-Atroshi et al. [19] developed a model that uses HOG with SVM for the Facial Expression Recognition in a improved manner. The support vector machine (SVM) algorithm is trained to detect the eyes and mouth regions from the face depending on histogram-oriented gradient (HOG)which is used as a features extractor. Then, merge the eyes and mouth regions for each image to create a new form of an image. After that, five different types of images are generated from the merged image named RGB, HSV, Gray, Binary, and YCBCR. The images are fedone by one into the convolution neural network (CNN) algorithm. The proposed system has been tested on threedifferent types of datasets (KDEF, JAFFE, and FER2013) and the prediction accuracy in the system has reached more than 98% in all used datasets.

H.M. Shahzad et al. [20] developed a hybrid model for emotion recognition using wo methods of CNN such as AlexNet and VGG-16. The methodology includes Alexnet architecture for training CNN model. The feature extraction is done using AlexNet and VGG-16. Decision Tree, Linear Discriminant Analysis, Support Vector Machine, K- Nearest Neighbor and Ensemble classifiers are used to predict the class of the data point and prediction of performance.

Ghalib et al. [21] developed a model that uses HOG and CNN for the Facial Expression Recognition. The HOG-CNN composed of three stages, median filter, HOG, and CNN. The first stage is preprocessing using median filter. They propose an approach for emotion recognition depending on facial expression using histogram of oriented gradients and convolution neural network (HOG-CNN). The second stage is feature extraction using HOG. The third stage is classification using CNN. The proposed method was tested and evaluated on the UMD face database. The system attained a high performance with a mean average accuracy of 98.07%, average precision of 94.78%, and average recall of 97.15%.

Sanjeev et al. [22] developed a model that uses LBP, CNN and frequency neural network for the Facial Expression Recognition. This research work provides a thorough and well-organized comprehensive comparative empirical study of facial expression recognition based on a deep learning study in frequency domain, convolution neural network, and local binary patterns features. They have attained the FER by incorporating neutral, joy, anger, fear, sadness, disgust, and surprise as seven universal emotional categories. This research could pave the way for a new approach to facial emotion identification in terms of accuracy and high-performance.

Lakshmi et al. [23] developed a facial emotion recognition system using modified HOG and LBP features combined with deep stacked autoencoders (DSAE). By focusing on key facial regions like the eyes, nose, and mouth, their approach achieved high accuracy, with 97.66% on the CK+ dataset.

Table 2.1 Summary of the Literature Survey

Reference	Proposed Method	Dataset Used	Results
D Hema et al, 2021	Patch-SIFT,ML classifier, Ensemble classifier, K-fold validation	JAFFE, CK+	Achieved an accuracy of 98%.
Vitoria et al,2021	Parameterized photograms and ML techniques.	CK+, MUG	CK+ 83.37% and MUG 72.55%.
Mundher et al,2017	Deep Learning Architecture, BAG classifier	CK+, FER2013	FER2013 73.4% and CK+ 99.1%.
Nirvair et al, 2016	Smoothing, Computational complexity of SIFT, Automatic Algorithm.	JAFFE	Accuracy of 76.05%.
Chieh-Ming et al,2018	Illumination Augmentation and direct training.	CK+	Achieved an accuracy of 74.20%.
Ali et al,2022	Feature Discriminator, Mean Discriminator, Embedding	RAFDB, FER2013	FER2013 71.48% and RAFDB 85.93%.

	Discriminator and corelation Matrix.		
Chang et al,2021	SACNN, LSTM, ALSTMSs.	FER2013, CK+, JAFFE	FER2013 74.31%, CK+95.15%, JAFFE 98.57%.
Tanoy et al,2022	Prepare Data, Identify during feature extraction and divide image into seven emotions.	JAFFE, CK+	JAFFE 92.05% and CK+ 98.13%.
Chahak et al,2022	HOG, SIFT.	CK+, JAFFE	HOG-CNN CK+ 98.48%, JAFFE 91.43% and SIFT-CNN CK+97.96%,JAFFE 82.85%.
Change et al,2018	MTCNN, SDM,SVM and STED.	AFEW	Achieved 61.87% accuracy.
Cuiping et al,2018	Geometric feature and Texture feature.	CK+, FER2013, RAF	FER2013 71.52%, CK+ 98.48% and RAF 87.34%.
B. Meena et al,2023	Random Forest, XG Boost.	FER	95% accuracy was achieved.
Zhong et al,2021	HOG-ESRs.	FER2013	Accuracy of 89.3% was achieved.
Saeed et al,2024	HOG feature, Random Forest classification.	JAFFE	92.97% accuracy was achieved.
Niu et al,2021	LBP, ORB	JAFFE, CK+, MMI	LBP 86.7% and ORB 89.2%.
Mukta et al,2019	ROI Extraction, Feature Vector Fusion, Classification.	JAFFE, CK+, MMI	CK+ 97%, MMI 88% and JAFFE 86%.

Julina et al,2019	HOG and LBP.	JAFFE	HOG 87% and LBP 64%.
Erlangga et al,2024	MobileNet-V2, Inception-V3.	FER	Inception-V3 96%,MobileNet-V2 89%.
Al-Atroshi et al,2023	HOG and SVM.	KDEF,JAFFE,FER2013	98% accuracy for all datasets.
HM Shahzad et al,2023	AlexNet, VGG-16.	FER	Accuracy of 62% was achieved.
Ghalib et al,2023	HOG and CNN.	UMD	98.07% was achieved.
Sanjeev et al,2023	LBP and CNN.	FER	85% accuracy was achieved.
Lakshmi et al,2021	HOG, LBP and DSAE.	CK+	HOG 93.30%, LBP 95.24%.

2.1 Gaps

Researchers focus on variety of approaches to reduce current gaps in facial emotion recognition. Enhancing robustness and generalization is prioritized by analysing real-time applications. CNN-SIFT models and other hybrid techniques maximize feature extraction and identification, while accuracy is increased by combining CNNs with handcrafted features like HOG, LBP, and ORB. For better accuracy HOG and SVM is analysed with deep learning methods. Incorporating geometric deformations, additional descriptors and dynamic features strengthens accuracy. These developments bridges the gap between handcrafted and the deep learning approaches by improving classifiers and feature extraction techniques.

CHAPTER 3

METHODOLOGY

3.1 Block Diagram

3.1.1 Traditional Methods

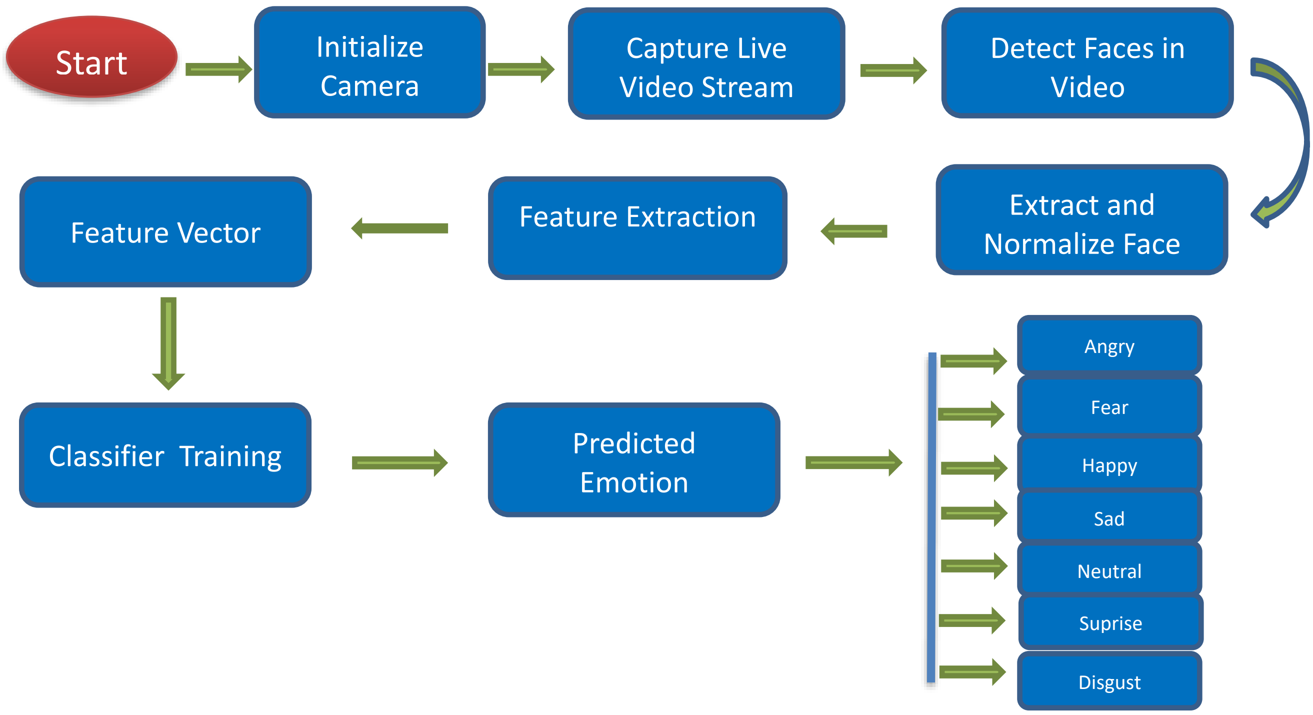

Figure 3.1 Traditional methods flow

Face Detection and Preprocessing is the crucial step in detecting the facial emotion recognition using machine learning. This step focus mainly on identifying faces in the input video and preparing them for the feature analysis. After detection, the faces are aligned, resized to get the consistent dimensions. This step includes adjustments in the variation in the size, lighting, orientation, or scale which ensures uniformity before the further processing. The accuracy of the model depends on the quality of the labelled data. Once the data has been pre-processed it can be split into training, validation and testing sets. The outcome of this process is that it detects the original image from the data.

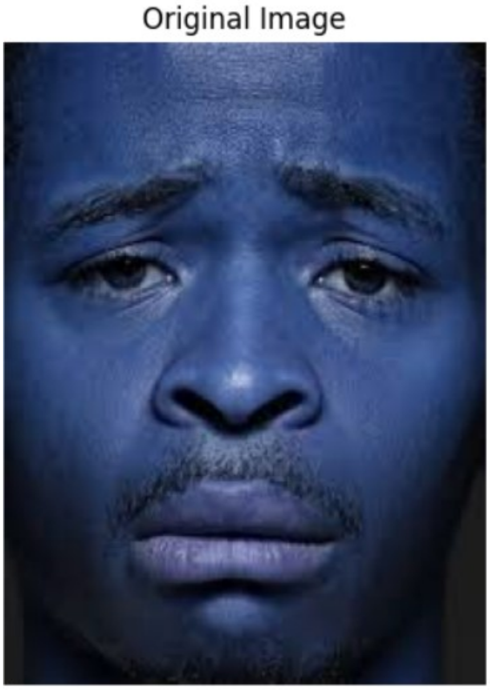

Figure 3.2 Snapshot of the original image detected.

Feature Extraction and Detection, this stage involves extracting the features from the detected original image and representing them in the way that can distinguish one face from the other. Feature extracting involves the techniques such as LBP, SIFT, ORB and HOG to highlight the edges in the face and the distinct patterns. Key points on the face such as eyes, mouth, nose are identified and the facial emotions are detected from the expressions of the original image detected. These are detected for the better representation of the emotions. CLAHE is applied as the pre-processing technique for the contrast of the original image. This makes the extracted features more prominent and improves the performance of the further extraction methods used in the detection of facial emotions.

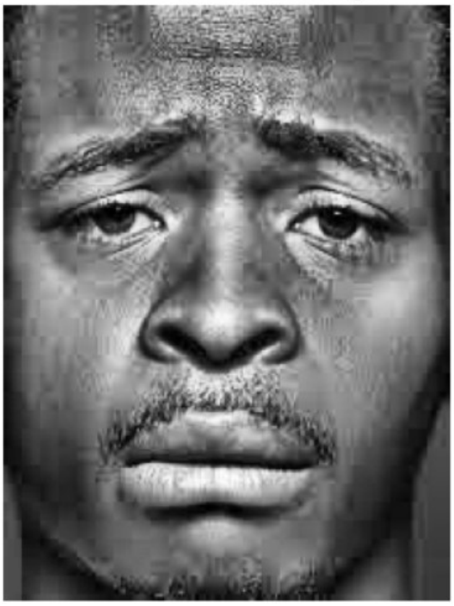

Figure 3.3 Snapshot of the CLAHE processed image.

Classification, this step involves using the extracted feature to train the machine learning model and to classify the faces. The features are passed to the classifiers in this step like the random forest, SVM. The model is trained using the labelled data and the classification predicts the class of the detected face based on the extracted features. The trained model classifies to detected the emotions of the facial expressions.

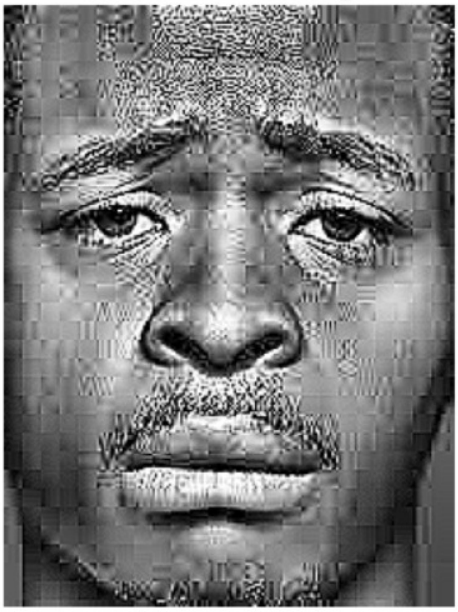

Figure 3.4 Snapshot of the final processed image.

3.1.2 Deep Learning Using CNN

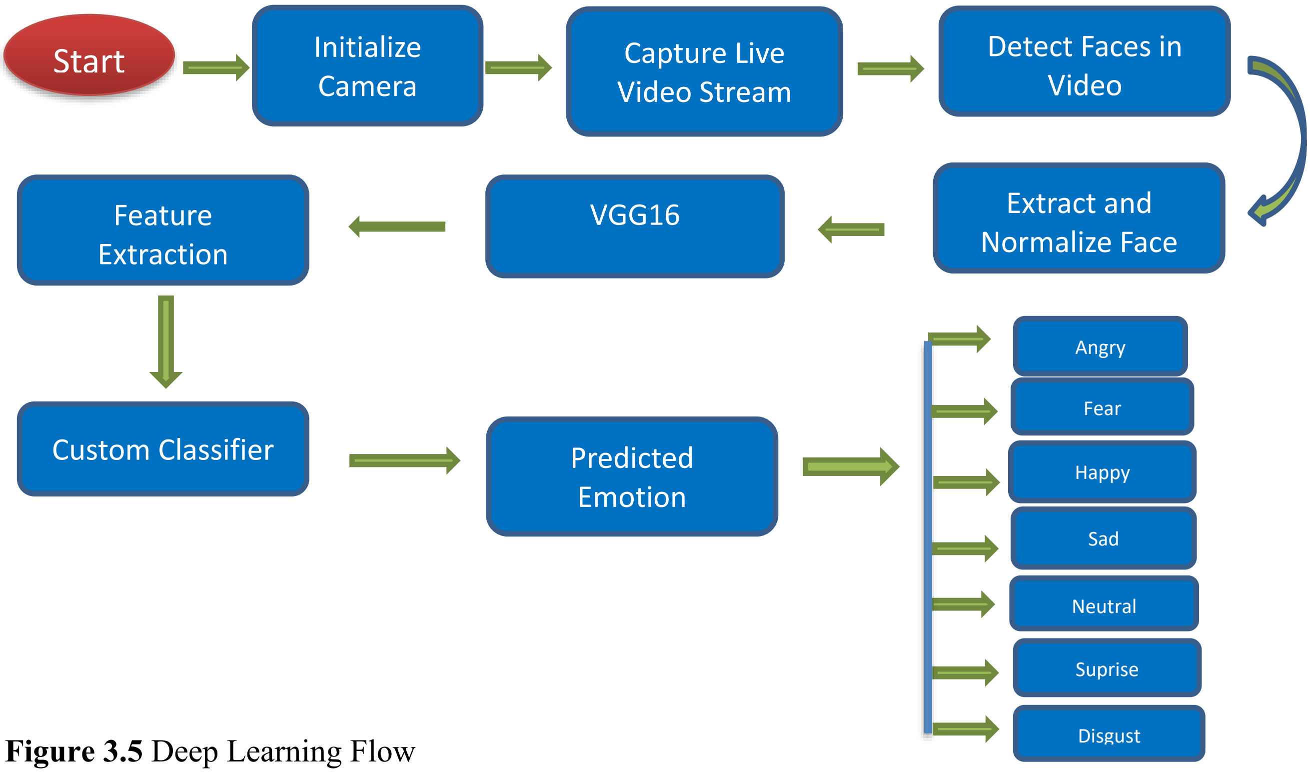

Figure 3.5 Deep Learning Flow

- Pre-processing of the data, this stage prepares the input for the deep learning model. Aligning and resizing of the image is obtained for the further processing to be fed into VGG16 model for the feature extraction. After the normalization of the image is done it is fed to the VGG16 model.

- Feature extraction and detection using VGG16, this includes a deep convolution neural network with 16 layers of architecture. Pre trained image is fed for the feature extraction. The convolution layers of VGG16 are used as feature extractors. These layers captures complex patterns, like edges and textures. This provides the semantic features of the faces.

- Classification using real-time, the extracted features from the VGG16 model are flattened in real-time for each face detected in video frame. The real time ensures the faster detection of facial emotions and are classified to the seven emotion class.

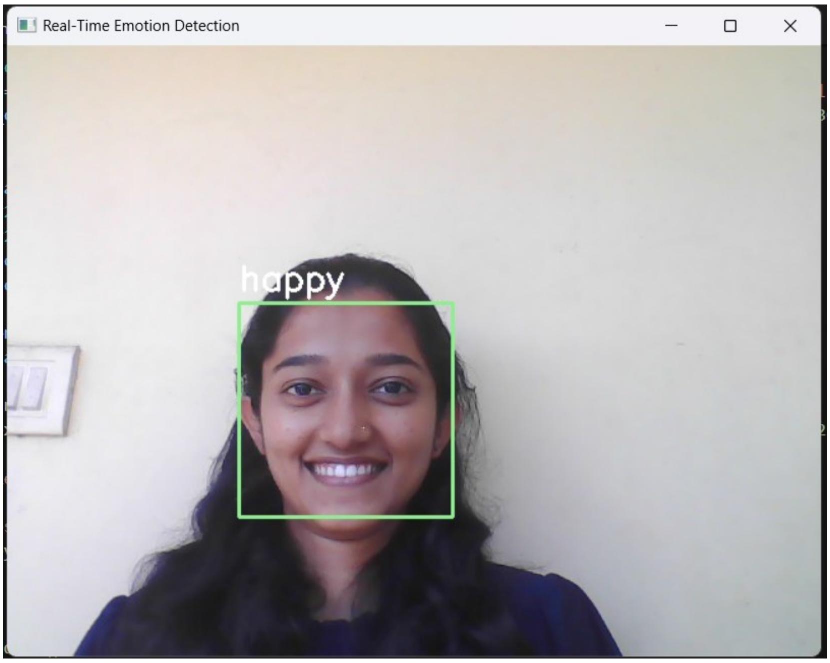

Figure 3.6 Snapshot of real-time emotion detection.

CHAPTER 4

SYSTEM DESIGN

4.1 Support Vector Machine (SVM)

Finding a hyperplane in an N-dimensional space (N- the number of features) that accurately categorizes the data points is the aim of the support vector machine algorithm. There are numerous hyperplanes that could be selected to divide the two groups of data points. Finding a plane with the highest margin that is, the maximum distance between data points of the two classes is our goal. By increasing the margin distance, we may increase the confidence with which future points can be classified. Decision boundaries known as hyperplanes in the data points.

The hyperplane is essentially a line if there are two input characteristics. The hyperplane turns into a two-dimensional plane when there are three input features. If there are more than three features, it gets hard to imagine. Data points that are closer to the hyperplane and have an impact on its orientation and location are known as support vectors. By employing these support vectors, we optimize the classifier's margin. There are two types of SVM.

Linear SVM: This classifier is used for linearly separable data, which is defined as data that can be divided into two classes using a single straight line. This type of data is known as linearly separable data.

Non-linear SVM: This type of SVM is used for data that is not linearly separated; that is, if a dataset cannot be categorized using a straight line, it is referred to as non-linear data, and the classifier that is employed is known as a non-linear SVM classifier.

4.2 Random-Forest Classifiers

It is an ensemble learning methos that uses multiple decision trees to make predictions, the majority of the votes is considered as the final predictions. Random forest works well with the numerical and the categorical data. It is not suitable for directly handling data without pre-extracted features. The extracted features from the images serve as the input to this classifier. Random forest would train multiple decision tree. These are better for the small datasets.

It not well suited as the VGG16 model for the emotion recognition. Random forest requires less computational power compared to the deep learning neural networks.

4.3 VGG16 (Visual Geometry Group 16-Layer Network)

VGG16 is the deep convolutional neural network (CNN) used for the image classification and the feature extraction. It deals with the large datasets and learns the hierarchical features from the raw images. It has the 16 layers. VGG16 is ideal for image processing as it directly processes the raw images to extract the deep features. The convolution layers of the VGG16 are used as the feature extractor. This model directly learns from the raw input eliminating the need for manual feature extraction.

4.4 Support Vector Classification (SVC)

It is the specific implementation of the SVM designed for the classification tasks. SVC handles the non-linear data with kernels. It scaled well for the smaller datasets. Like SVM even SVC require the pre-extracted features from the dataset. Support Vector Classification is more suited for tasks like facial emotion classification but only after the features are extracted.

4.5 CLAHE (Contrast Limited Adaptive Histogram Equalization)

It is the preprocessing techniques for the contrast of the images. It is particularly used for the images with the uneven lighting or the low contrast. Here the image is divided into the smaller regions called grids. Each grid is processed independently, enhancing the contrast. CLAHE can help to improve the accuracy of the facial emotion recognition in low-light or shadow conditions.

CHAPTER 5

RESULTS AND DISCUSSION

The strengths of several feature extraction methods in facial emotion identification are demonstrated by the comparison of model accuracies.

5.1 Local Binary Pattern

- A labelled dataset is divided into training and testing sets for the facial emotion recognition system. Grayscale conversion and CLAHE are used to preprocess the images for contrast enhancement, while Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) are used to extract features.
- Two machine learning models Random Forest and SVM (with hyperparameter adjustment via Grid Search CV) are trained using these features after they have been normalized and reduced using PCA.
- Metrics like as confusion matrices and accuracy are used to assess the models. Additionally, a visualization component facilitates interpretability by highlighting intermediate feature extraction phases.
- Emotion detection using this technology is guaranteed to be effective, precise, and interpretable. The accuracy obtained by this approach is 62.69%.

```
Tabnine | Edit | Test | Explain | Document | Ask
def get_features(image, radii=None, n_points_multiplier=8, method='uniform', normalize=True):
    if radii is None:
        radii = [1, 2, 3]

    gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

    # contrast enhancement
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))
    gray_image = clahe.apply(gray_image)

    lbp_features = []

    # LBP features
    for radius in radii:
        n_points = n_points_multiplier * radius
        lbp_image = local_binary_pattern(gray_image, n_points, radius, method)
        lbp_histogram, _ = np.histogram(
            lbp_image.ravel(), bins=np.arange(0, n_points + 3), range=(0, n_points + 2)
        )
        lbp_histogram = lbp_histogram.astype("float") / (lbp_histogram.sum() + 1e-6)
        lbp_features.append(lbp_histogram)

    lbp_feature = np.concatenate(lbp_features)

    # HOG features
    hog_features = hog(gray_image, orientations=9, pixels_per_cell=(8, 8),
                       cells_per_block=(2, 2), block_norm='L2-Hys')


    # Combine both features
    return np.concatenate((lbp_feature, hog_features))
```

Figure 5.1 Snapshot of LBP extraction feature

Figure 5.2 CLAHE enhanced image.

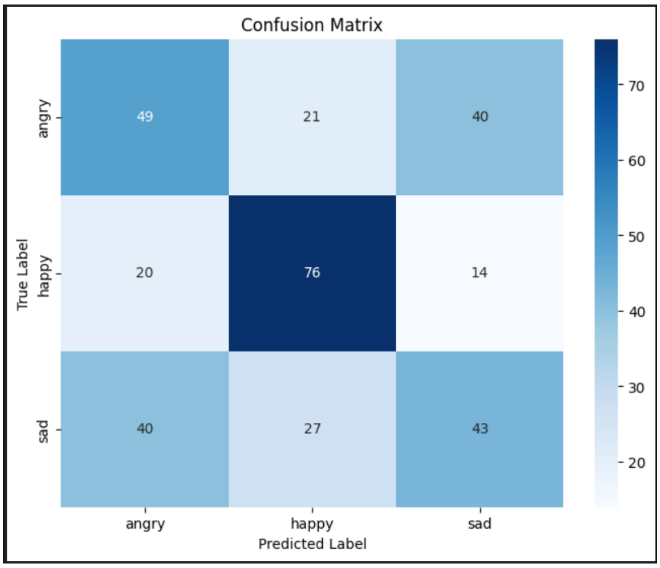

Figure 5.3 Snapshot of Confusion Matrix for LBP.

5.2 Scale-Invariant Feature Transform (SIFT)

- As part of the technique, the dataset is categorized into directories based on emotions (such as angry, happy, and sad) and assigned numerical labels.
- Preprocessing techniques include grayscale conversion, gamma correction for brightness control, sharpening for edge emphasis, and CLAHE for contrast enhancement. Dataset diversity is increased using augmentation techniques like horizontal flipping.
- Two techniques are used to extract features: deep features using a pre-trained ResNet50 model for high-level representations, and classic descriptors (SIFT and ORB) for texture-

based key points. Features are extracted from pre-processed and enhanced images, standardized, and divided into training and testing sets.

- To find the ideal number of trees, depth, and features, a Random Forest classifier is trained using Grid Search CV's hyperparameter optimization. Metrics for model evaluation include confusion matrices for performance visualization and accuracy. This strategy works well. The accuracy obtained for this SIFT and HOG extraction feature is 72.43%.

```
def extract_descriptors(image):

    sift = cv2.SIFT_create()
    orb = cv2.ORB_create()


    sift_descriptors = sift.detectAndCompute(image, None)[1]
    orb_descriptors = orb.detectAndCompute(image, None)[1]

    if sift_descriptors is not None and orb_descriptors is not None:
        return np.vstack((sift_descriptors, orb_descriptors))
    return sift_descriptors if sift_descriptors is not None else orb_descriptors

Tabnine | Edit | Test | Explain | Document | Ask
def extract_deep_features(image, model):
    """Extract deep features using a pre-trained ResNet50 model."""
    resized_image = cv2.resize(image, (224, 224))

    if len(resized_image.shape) == 2 or resized_image.shape[2] == 1:
        resized_image = cv2.cvtColor(resized_image, cv2.COLOR_GRAY2RGB)

    image_array = img_to_array(resized_image)
    image_array = np.expand_dims(image_array, axis=0)
    image_array = preprocess_input(image_array)
    features = model.predict(image_array)
    return features.flatten()
```

Figure 5.4 Snapshot of SIFT-ORB extraction Features.

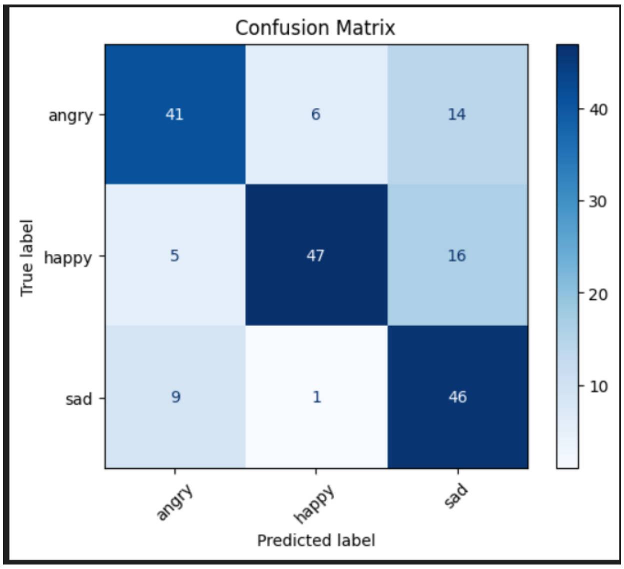

Figure 5.5 Snapshot of Confusion Matrix for SIFT-ORB.

5.3 Oriented FAST and Rotated BRIEF

- This code uses OpenCV's ORB (Oriented FAST and Rotated BRIEF) method to process an input image. After reading an image and converting it to grayscale, it uses ORB to identify key-points, or features.
- Green circles are then superimposed on the grayscale image to visualize the key-points that have been identified. Within a designated output directory, the original and processed photos are stored in distinct subfolders called Original Images and Processed Images.
- Subfolders are generated dynamically if they don't already exist. Additionally, the script waits for the user to hit a key before closing the windows, displaying both the original image and the processed image with key-points in other windows.
- At startup, ORB has a maximum of 200 features. The feature makes sure that errors are handled when reading images, makes visualization simple, and storage of results. The accuracy obtained for this ORB feature is 73.11%.

```
def process_sample_image(image_path, output_folder, orb):
    img = cv2.imread(image_path)
    if img is None:
        print("Error reading image!")
        return

    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    keypoints, descriptors = orb.detectAndCompute(gray, None)
    img_with_keypoints = cv2.drawKeypoints(gray, keypoints, None, color=(0,255,0), flags=0)

    original_output_folder = os.path.join(output_folder, "Original_Images")
    if not os.path.exists(original_output_folder):
        os.makedirs(original_output_folder)
    original_output_path = os.path.join(original_output_folder, os.path.basename(image_path))
    cv2
    processed_output_folder = os.path.join(output_folder, "Processed_Images")
    if not os.path.exists(processed_output_folder):
        os.makedirs(processed_output_folder)
    processed_output_path = os.path.join(processed_output_folder, os.path.basename(image_path))
    cv2.imwrite(processed_output_path, img_with_keypoints)

    cv2.imshow("Original Image", img)
    cv2.imshow("Processed Image with Keypoints", img_with_keypoints)
```

Figure 5.6 Snapshot of code for ORB features.

Figure 5.7 ORB enhanced image.

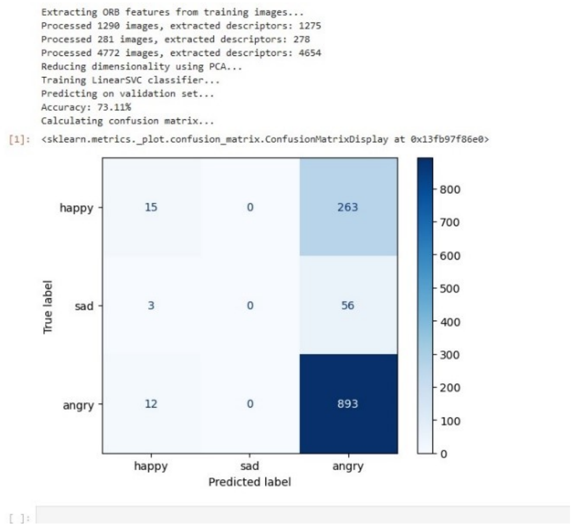

Figure 5.8 Confusion Matrix for ORB.

5.4 Histogram of Oriented Gradient (HOG)

- This code uses a Support Vector Machine (SVM) classifier and HOG (Histogram of Oriented Gradients) features to construct a facial emotion detection algorithm. Data is first loaded from a hierarchical folder, with subfolders standing in for various emotion categories. Every image is named according to its folder, scaled to a consistent size, and read in grayscale.
- The preprocessing pipeline uses illumination correction (to balance lighting), normalization (scaling pixel values to [0, 1]), denoising (with Gaussian blur), and CLAHE (to improve contrast) to improve image quality. Each image's HOG features are then retrieved, preserving texture and local edge information in a fixed-length feature vector.

- To make labels compatible with machine learning models, they are numerically encoded. The HOG features are used to train an SVM with a linear kernel from the test dataset and assessed on the training dataset. Lastly, accuracy is calculated, which shows how well the model can categorize emotions. The accuracy obtained for this feature is 63.78%.

```
def extract_features(images):

    images_uint8 = [np.uint8(img * 255) if img.max() <= 1 else img for img in images]
    return np.array([compute_hog_features(img) for img in images_uint8])


Tabnine | Edit | Test | Explain | Document | Ask
def resize_images(images, target_size=(48, 48)):
    return [cv2.resize(img, target_size, interpolation=cv2.INTER_AREA) for img in images]

Tabnine | Edit | Test | Explain | Document | Ask
def normalize_images(images):
    return [img / 255.0 for img in images]

Tabnine | Edit | Test | Explain | Document | Ask
def apply_clahe(images):
    clahe = cv2.createCLAHE(clipLimit=4.0, tileGridSize=(8, 8))
    return [clahe.apply(img) for img in images]

Tabnine | Edit | Test | Explain | Document | Ask
def denoise_images(images):
    return [cv2.GaussianBlur(img, (5, 5), 0) for img in images]

Tabnine | Edit | Test | Explain | Document | Ask
def correct_illumination(images):
    corrected_images = []
    for img in images:
        img_blur = cv2.GaussianBlur(img, (21, 21), 0)
        img_corrected = cv2.addWeighted(img, 4, img_blur, -4, 128)
        corrected_images.append(img_corrected)
    return corrected_images
```

Figure 5.9 Snapshot for HOG feature extraction.

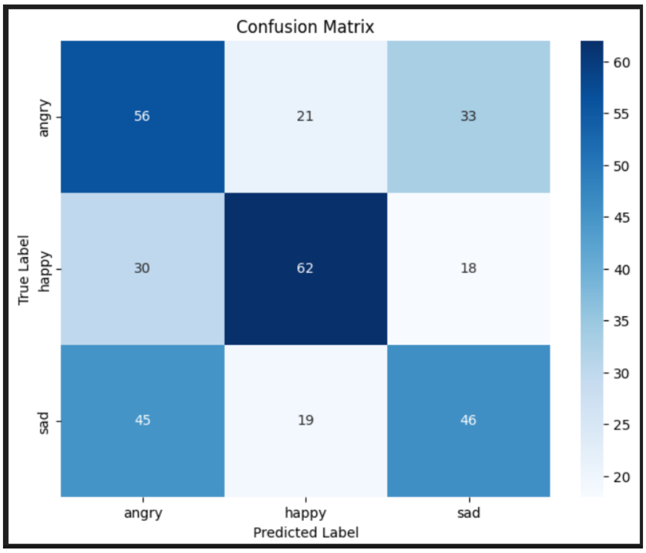

Figure 5.10 Snapshot of the Confusion Matrix for HOG.

We have proposed the Deep learning approaches, Convolution Neural Network (CNN) have been used in comparison to the traditional facial emotion recognition model.

5.5 Convolution Neural Network (CNN)

This study's facial emotion identification methodology includes a number of crucial components. After loading the dataset, each image is pre- processed by scaling it to a specific dimension and normalizing the pixel values. The photographs are then arranged into named directories that reflect various moods. Label Encoder is used to encode the emotion labels, and one-hot encoding is used to get the labels ready for classification. To avoid overfitting and add diversity to the model, data augmentation techniques including rotation, shifting, and horizontal flipping are applied to the training data. The top layers are swapped out for a unique architecture made for emotion classification, while the base is a pre-trained VGG16 model that uses its deep convolutional layers to retrieve information. Additionally, the model is improved with GlobalAveragePooling2D.

Using the Adam optimizer, which has a low learning rate and categorical cross-entropy loss for multi-class classification, the model is assembled for training. Callbacks for early pausing and learning rate decrease are used to keep an eye on the model's performance and avoid overfitting. Metrics including accuracy, precision, recall, and the confusion matrix are used to evaluate the model's performance on a validation set following training. A 81.18% accuracy rate was attained. Callbacks such as early stopping and learning rate reduction proves in preventing overfitting. These allows model to halt train once it reaches the optimal ability.

```
'data agumentaion'
data_gen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True
)

"vgg16 model"
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(image_size[0], image_size[1], 3))

"buliding a model"
model = Sequential([
    base_model,
    GlobalAveragePooling2D(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(num_classes, activation='softmax')
])

"compiling the model"
model.compile(optimizer=Adam(learning_rate=0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

"call backs"
lr_reducer = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=5, min_lr=1e-6)
early_stopper = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)
```

Figure 5.11 Snapshot of extraction features of CNN.

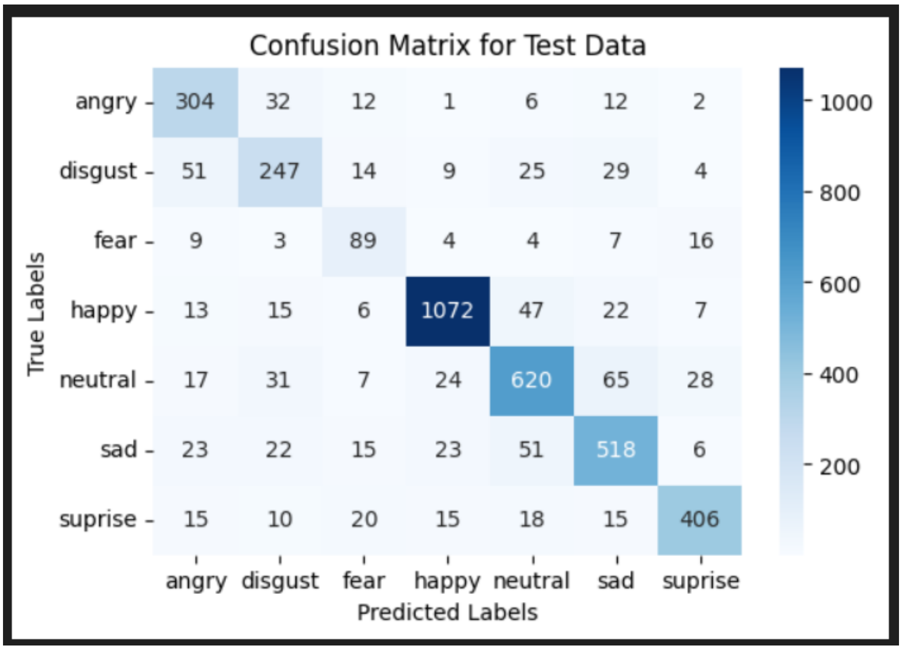

Figure 5.12 Snapshot of Confusion Matrix of CNN.

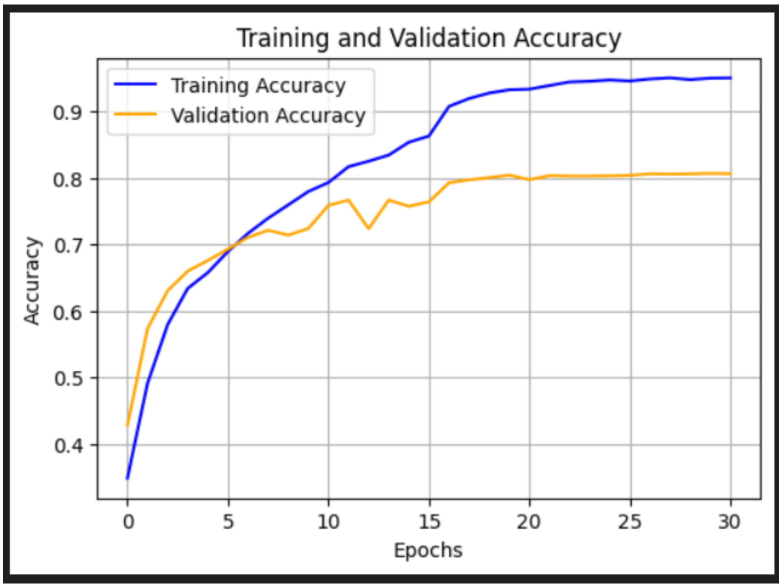

Figure 5.13 Snapshot of Accuracy trends during model training.

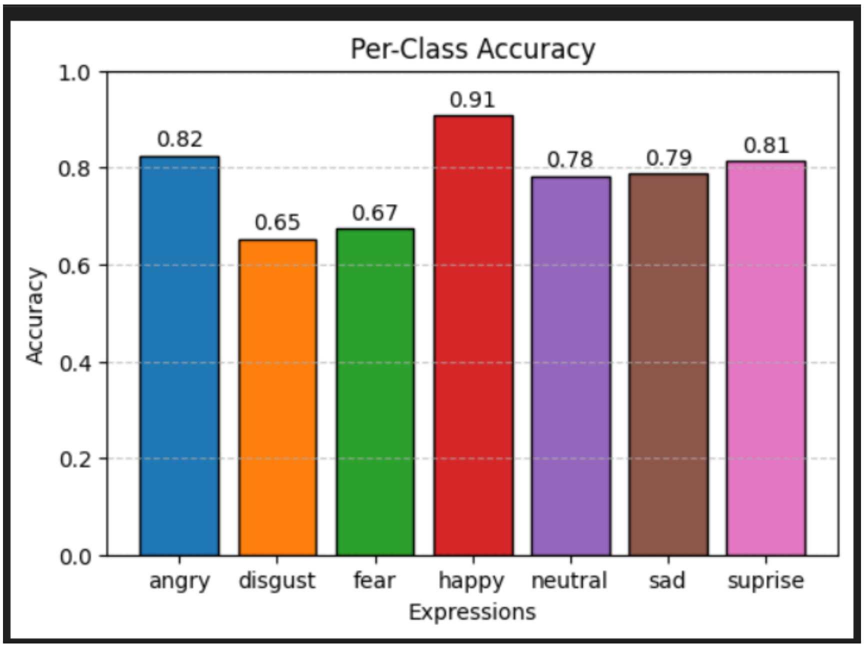

Figure 5.14 Snapshot of accuracy distribution across emotion class.

Table 5.l: Models of Facial Emotion Recognition

Algorithm	Recognition Rate
Local Binary Pattern (LBP)	**62.69%**
Scale-Invariant Feature Transform (SIFT)	**72.43%**
Oriented FAST and Rotated BRIEF (ORB)	**73.11%**
Histogram of Oriented Gradient (HOG)	**63.78%**
Convolution Neural Network (CNN)	**81.18%**

In the Table 5.1 it shows the best accurate algorithm for the facial emotion recognition. The CNN has the most accurate value for the facial emotional recognition. Because CNNs can automatically acquire hierarchical features from raw image data through numerous levels of processing, they are able to grasp intricate patterns and spatial relationships within the image, which accounts for their superior performance. This is in contrast to traditional approaches, which mostly rely on manually created characteristics (such textures and key-points) and are frequently not able to manage changes in positions, lighting, or facial expressions or to provide the generalised accuracy.

CHAPTER 6

CONCLUSION

In conclusion, by contrasting conventional approaches with the more sophisticated Convolutional Neural Networks (CNNs), this study provides a thorough assessment of facial emotion identification methodologies. Because of their ease of use and efficiency in feature extraction, traditional methods including Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), Oriented FAST and Rotated BRIEF (ORB), and Histogram of Oriented Gradient (HOG) have long been dependable. The best-performing conventional approach was ORB, which had the highest accuracy of 73.11% among them. These techniques, however, are limited in their capacity to generalize across a variety of complicated datasets due to their heavy reliance on manually created features, especially when handling complex facial expressions or variable environmental conditions.

However, CNNs have shown their revolutionary potential as a deep learning technique by obtaining an outstanding 79% accuracy on the FER-2013 dataset. CNNs can recognize subtle and intricate features in facial expressions because, in contrast to conventional techniques, they can automatically learn hierarchical patterns from data. CNNs are a more flexible and potent tool for emotion recognition because of this flexibility, which enables them to adjust to big datasets containing a wide range of complex facial expressions.

CNNs' remarkable performance highlights their potential in a wide range of real-world applications. For example, CNNs can be used to identify stress, anxiety, and early signs of depression through facial expression analysis in mental health monitoring; similarly, CNN-powered emotion-aware systems in human-computer interaction can develop adaptive interfaces that react to user emotions in real time, improving the user experience; and in the customer service industry, facial emotion recognition can assist in analysing customer emotions to provide personalized experiences and increase satisfaction. Additionally, CNNs are especially well-suited for real-time emotion detection because of their capacity to process large volumes of data effectively and extract meaningful patterns, which opens the door for the deployment of CNN-based systems in fields like video surveillance, autonomous vehicles, and education.

Fundamentally, the development of face emotion identification methods bridges the gap between human emotions and robots, marking an important turning point in artificial intelligence. The incorporation of emotionally intelligent systems will open the door for more effective, flexible, and sympathetic solutions in a variety of industries as AI develops. Future advancements in facial expression identification, building on the groundwork established by this study, have the potential to revolutionize how we engage with technology and one another, creating a more cohesive and sensitive society.

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