Beyond Traditional Models: A Multi-classifier Learning Paradigm for Emotion Recognition Using MFCC Features

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***Abstract*—In recent years, real-time facial and emotion recognition has attracted notable attention due to its diverse applications in security, healthcare, education, and human-computer interaction. This work introduces a modern emotion recognition system capable of detecting and classifying seven basic emotions: happiness, anger, sadness, surprise, neutrality, fear, and disgust. The suggested system applies artificial intelligence and machine learning techniques to examine and process facial images, converting them into signals and deriving distinctive features using Mel-Frequency Cepstral Coefficients (MFCC), a method commonly used in speech analysis but seldom applied in facial emotion recognition. This innovative feature extraction approach is combined with classification using five algorithms: Logistic Regression (LR), K-Nearest Neighbors (KNN), Random Forest (RF), Artificial Neural Networks (ANN), and Support Vector Machine (SVM). The system's performance is assessed using standard measures, including Accuracy, Matthews Correlation Coefficient (MCC), F1-Score, specificity, recall, and precision. Experimental findings show that the RF classifier reached the highest accuracy of 99.96%, exceeding other models, while SVM achieved the lowest accuracy at 86.88%. These outcomes highlight the system's capability to improve real-time emotion detection applications and contribute effectively to ongoing research trends.**

***Index Terms*—classification, emotion detection, machine learning, Mel-frequency cepstral coefficients**

I. Introduction

Emotion plays a vital role in human communication, influencing decision-making, behavior, and interpersonal interactions. With the rise of Artificial Intelligence (AI) and ubiquitous computing, the ability to detect emotions in real-time has become increasingly valuable across various domains, including healthcare, education, entertainment, and human-computer interaction [1]. Real-time emotion detection systems aim to identify and classify emotional states from various modalities, including facial expressions, voice, and text, using Machine Learning (ML) and deep learning techniques [2]. The traditional emotion recognition methods often rely on static data and single-modality inputs, which limit their effectiveness in dynamic, real-world environments. Recent deep learning advances have enabled multimodal systems that analyze live video, audio, and text with high accuracy and low latency [3].

Recent advancements in real-time emotion detection have leveraged deep learning and embedded systems to enhance accuracy and responsiveness across various applications. Pillai and Chellappan [4] developed a face recognition system using Dlib's ResNet-34 model integrated with Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) classifiers on a Raspberry Pi 4. Their system achieved 96% accuracy and 100% recall, demonstrating robust performance in intruder detection scenarios. Zedan *et al.* [5] proposed an IoT-based emotional recognition system for controlling embedded devices, utilizing HOG and SVM to classify smiling versus non-smiling expressions. Their model achieved an 89% recognition rate using 10-fold validation on the GENKI-4K dataset, enabling remote control of devices like alarms and doors. Dudekula and Purnachand [6] evaluated facial emotion recognition using NVIDIA Jetson Nano, comparing Extreme Inception (Xception), Visual Geometry Group-19 (VGG-19), and an open-source computer vision library (OpenCV) model. VGG-19 achieved the highest accuracy at 98.4%, followed by Xception at 97.1%, and OpenCV at 95.6%, highlighting the effectiveness of deep learning models in real-time applications. Kamera *et al.* [7] developed a real-time multimodal emotion recognition framework in which facial emotions were detected using a 2D Convolutional Neural Network (2D-CNN). The facial recognition module achieved a validation accuracy of 98.48%, demonstrating the effectiveness of deep learning techniques for real-time applications.

Agung *et al.* [8] proposed Convolutional Neural Network (CNN)-based facial emotion recognition models using transfer learning with pre-trained Inception-V3 and MobileNet-V2 architectures, as well as a custom CNN optimized through the Taguchi method for hyperparameter tuning. The proposed approach achieved an accuracy of 96% and an average F1-Score of 0.95.

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Aka *et al.* [9] presented an IoT-enabled humanoid robot integrating voice control and face recognition using Edge Impulse and deep learning. Their system demonstrated high accuracy in voice and facial recognition tasks, supporting assistive interactions. Martínez and Vega [10] developed a Robot Operating System (ROS-based) facial emotion detection system using MediaPipe Face Mesh and geometric analysis on Raspberry Pi 4. Their model achieved real-time performance at over 13 Frames Per Second (FPS) and showed strong results with K-Nearest Neighbors (KNN), SVM, and Multilayer Perceptron (MLP) classifiers. Lastly, Zamir *et al.* [11] employed CNN-based face detection and recognition on Raspberry Pi, achieving 98% accuracy on the Virtual Makeup (VMU) dataset and 95.71% on the 14 Celebrity dataset, confirming the reliability of CNNs in real-time surveillance and recognition tasks.

Mrabet *et al.* [12] focused on developing a Machine Learning (ML) model based on You Only Look Once (YOLOv5) to detect whether people are wearing masks. The system aims to verify whether individuals are wearing them correctly, incorrectly, or not at all. This model was specifically designed for use in high-risk environments for Coronavirus disease (COVID-19) transmission, such as laboratories, healthcare facilities, and public spaces, where compliance with mask-wearing is critical. The system achieved an average precision of 99%. Aly [13] presented an innovative facial expression recognition system based on a residual network with 50 layers (ResNet50), Temporal Convolutional Networks (TCNs), and Convolutional Block Attention Module (CBAM) techniques, where the ResNet50 model excels. The accuracy was 91.86%, 91.71%, 95.85%, and 97.08% on the Real-world Affective Faces Database (RAF-DB), Facial Expression Recognition 2013 (FER-2013) dataset FER2013, Cohn-Kanade dataset (CK+), and Karolinska Directed Emotional Faces (KDEF) datasets, respectively.

Tuan *et al.* [14] developed a CNN-based real-time facial emotion recognition framework enhanced with Haar Cascade face detection. Using a dataset containing five emotion classes, the proposed system achieved a testing accuracy of 85.47% and demonstrated reliable performance in real-time emotion analysis. Ismael *et al.* [15] present a model, "deep learning-based real-time face recognition system". The model focused on developing an evident-opportunity first acknowledgment structure utilizing an association of deep and machine intelligence actions. The methods involved complex use of HOG for face recognition on mathematical representations, resorting to a personalized first milestone process to assemble the first fields, and utilizing an SVM to discover faces, establishing 128 embeddings. The system obtained a powerful 96.88% accuracy and a frame rate of nearly three frames per second when judged against a table of 40 Pictures of eight different crowds.

Subramanian *et al.* [16] developed a face and emotion recognition system based on machine learning and artificial intelligence. The introduced model consists of three stages: data acquisition, feature detection, and emotion classification. The model was trained using Gradient Boosting (GB) and achieved an average accuracy of 99%. On the other hand, Adimoolam *et al*. [17] proposed a hybrid model combining Densely Feature selection Convolutional Neural Network with Hyperparameter tuning (DFCNHP), a hybrid protocol that achieves high accuracy and faster prediction times. The system was designed to operate efficiently in both static and dynamic environments and achieved 98% accuracy with a prediction time of 1.11 s. The article in Ref. [18] represents an Internet of Medical Things (IoMT) based facial emotion detection and recognition system. This system was constructed by utilizing a Raspberry Pi with the assistance of a CNN. Physiological sensors were used to conduct experimental study on the facial expressions of human beings, along with their emotional expression status of human beings. Then, a model was proposed for the detection of emotions in real-time on a Raspberry Pi, along with the Intel Movidius Neural Compute Stick 2 (NCS2). The accuracy of facial expression detection varied from 56% to 73% using several models. A test was performed to extract the large differences in diastolic and systolic blood pressure and the heart rate of an individual for neutral, angry, and happy emotions.

This research introduces a novel hybrid deep learning and machine learning framework for real-time emotion detection that integrates both signal processing and computer vision techniques to enhance classification accuracy, computational efficiency, and cross-modal adaptability. Unlike conventional emotion recognition systems that rely solely on visual or auditory data, the proposed model innovatively transforms facial images into signal representations, enabling the extraction of frequency-based features using Mel-Frequency Cepstral Coefficients (MFCC). This approach, traditionally used in speech and audio analysis, is repurposed here to capture subtle emotional cues embedded in visual data, offering a unique perspective on emotion representation. To ensure robust classification, the system incorporates a diverse ensemble of machine learning algorithms, including Logistic Regression (LR), KNN, Random Forest (RF), Artificial Neural Networks (ANN), and SVM. These classifiers are trained and evaluated on MFCC-derived features to determine the most effective model for real-time emotion recognition.

The novelty of this work lies in exploring facial emotion recognition through a unified MFCC-based multi-classifier framework. While MFCC has previously been applied in various image-processing domains, this study focuses on assessing its effectiveness for the recognition of seven fundamental facial emotions and systematically comparing the performance of five machine learning classifiers using the same feature representation. This integrated framework provides a comprehensive evaluation of classifier behavior and highlights the potential of MFCC-derived features as discriminative descriptors for facial emotion recognition. The research is structured into four main sections: Introduction, Methodology, Results and Performance Evaluation, and Conclusion, providing a comprehensive overview of the

system's design, implementation, and empirical validation.

II. Proposed Model

The proposed model aims to develop a comprehensive system capable of accurately detecting faces and recognizing facial expressions. As illustrated in Fig. 1, the system operates through six essential stages: image acquisition, image enhancement, signal conversion, feature extraction, emotion classification, and performance evaluation. Initially, the facial images dataset was selected and preprocessed using normalization and Region-of-Interest (ROI) extraction techniques to improve image quality and minimize noise. To prevent data leakage, the dataset was split at the raw image level prior to the 1D signal transformation, ensuring a rigorous evaluation under the 10-fold cross-validation protocol. Afterward, signal conversion and overlapping frames 65% overlap were performed separately in each of the data partitions. This resulted in situations where the frames from the same image ended up in one partition and were not split between training and testing sets. MFCCs were employed to extract the most discriminative features of facial expressions by analyzing the spectral properties of the generated signals.

The extracted features are subsequently used to train and evaluate five machine learning classifiers, including LR, KNN, RF, ANN, and SVM, to classify seven distinct emotions: anger, happiness, sadness, neutrality, surprise, fear, and disgust. The classifiers were selected based on their demonstrated effectiveness in addressing classification tasks involving diverse data characteristics. For instance, Random Forest (RF) is widely recognized for its robustness and its ability to handle high-dimensional datasets efficiently.

The performance of the proposed model was assessed using a confusion matrix and several evaluation metrics, including F-measure, specificity, accuracy, Matthews Correlation Coefficient (MCC), precision, and sensitivity. This multi-model approach provides a robust comparison and validates the effectiveness of the MFCC-based feature extraction technique in real-time emotion recognition.

A. Overview of the Dataset

The FER-2013 open-access dataset [19] used in this study contains 3589 facial images categorized into seven emotional states: anger, happiness, sadness, neutral, surprise, fear, and disgust. Each sample is represented as a 48 × 48-pixel grayscale facial image. Although the original dataset contains 3589 images, the number of samples is not uniformly distributed across the seven emotion classes. To avoid class imbalance and ensure a fair evaluation of the proposed model, a balanced subset consisting of 3157 images was selected, with equal representation from each emotion category. Representative examples from the dataset are presented in Fig. 2.

B. Image Preprocessing Pipeline

To enhance the quality and consistency of the input data, a comprehensive preprocessing pipeline is applied before feature extraction and classification. This process begins with normalization, which standardizes pixel intensity across all images to ensure uniformity and reduce variability caused by lighting conditions. Thresholding and binarization are then used to convert grayscale images into binary format, simplifying the data and emphasizing key facial features. To further refine the image quality, filtering techniques are employed: the Median filter effectively reduces noise while preserving important edges, and the Prewitt edge detection algorithm highlights structural boundaries and contours within facial regions. These preprocessing steps collectively improve the clarity, feature richness, and overall suitability of the images for subsequent signal conversion and emotion classification.

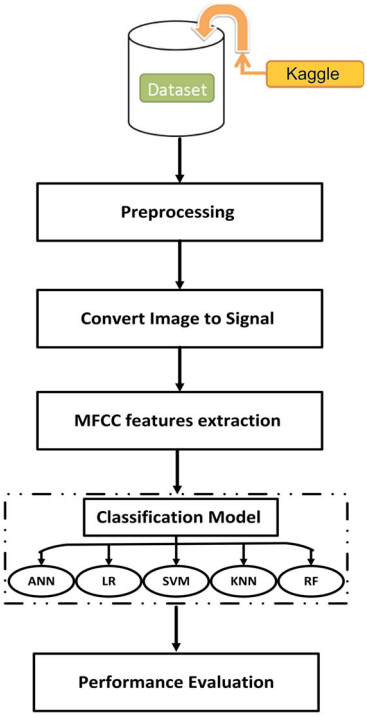


Fig. 1. The system's workflow.

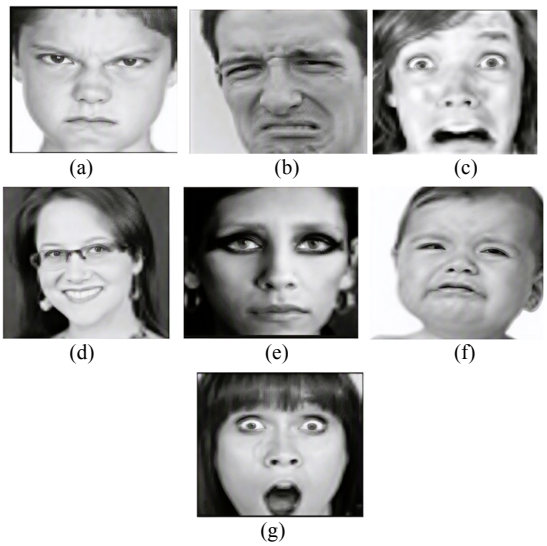


Fig. 2. Sample of image dataset: (a) angry, (b) disgusted, (c) fearful, (d) happy, (e) neutral, (f) sad, and (g) surprised.

C. Feature Extraction Using MFCC

The MFCC technique is widely regarded as one of the most effective methods for frequency-domain feature extraction in signal processing. Its strength lies in the use of the Mel scale, which distributes frequency bands in a manner that closely aligns with human auditory perception. MFCCs capture the spectral characteristics of signals, providing a compact and discriminative feature set that is highly suitable for emotion classification. Although Mel-Frequency Cepstral Coefficients (MFCCs) were originally developed for speech signal analysis, recent studies have demonstrated their effectiveness in a variety of image-processing applications. MFCC-based features have been successfully employed in chest X-ray image classification, pneumonia detection, hand-gesture recognition, and surface crack detection, highlighting their ability to capture discriminative spectral characteristics from visual data when appropriate signal representations are used [20, 21].

It should be noted that the contribution of this work does not stem from introducing MFCC to image processing for the first time, but rather from investigating its effectiveness for facial emotion recognition and systematically evaluating its performance across multiple machine-learning classifiers.

As illustrated in Fig. 3, the proposed model follows a structured sequence of steps, beginning with the conversion of facial images into signal representations. These signals are then segmented into overlapping frames, specifically, 40 frames of 1500 samples each, with a frame shift of 256 samples. This configuration results in approximately 65% overlap between adjacent frames, ensuring continuity and preserving temporal features.

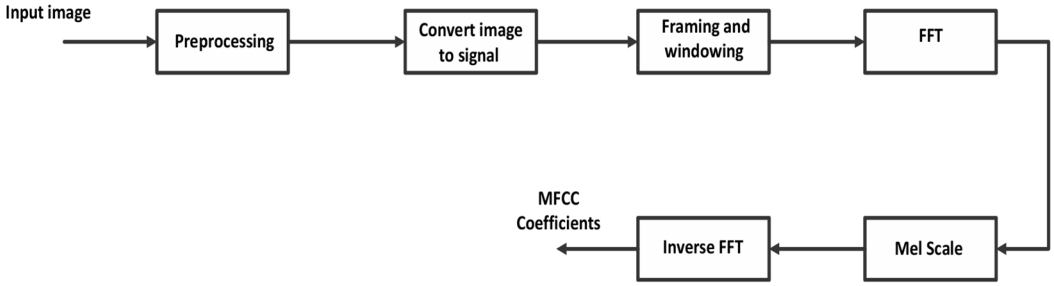


Fig. 3. General structure of MFCC feature extraction [22].

Following the framing stage, a Hamming window is applied to each frame to minimize spectral leakage as described in the script of Fig. 4. The windowed signals are then transformed using the Discrete Fourier Transform (DFT), producing a frequency spectrum that serves as input to a Mel-scale filter bank composed of 20 filters. Each filter emphasizes a specific frequency band according to the Mel scale, which is computed using the widely adopted formula:

$$f_{\text{mel}} = 2595\log_{10}\left(1+\frac{f}{700}\right) \quad (1)$$

```
%---------------------------FRAMING & WINDOWING---------------------------
frame_length_inSample=(Fs/1000)*Window_Length;
framedsignal=buffer(signal,frame_length_inSample,frame_length_inSample/2,..
    'nodelay')';
w=hamming(frame_length_inSample);
y_framed=framedsignal.*repmat(w',size(framedsignal,1),1);
size(y_framed);
%-------------------------------------------------------------------------
f=(Fs/2)*linspace(0,1,NFFT/2+1);
fmel=2595*log10(1+f./700); % CONVERTING TO MEL SCALE
fmelmax=max(fmel);
fmelmin=min(fmel);
filbandwidthsmel=linspace(fmelmin,fmelmax,No_Filter+2);
filbandwidthsf=700*(10.^(filbandwidthsmel/2595)-1);
fr_all=(abs(fft(y_framed',NFFT))).^2;
fa_all=fr_all(1:(NFFT/2)+1,:)';
filterbank=zeros((NFFT/2)+1,No_Filter);
```

Fig. 4. Script of the framing and windowing process.

This transformation maps linear frequency values to the Mel scale, enhancing the perceptual relevance of the extracted features. The output of the filter bank is the Mel spectrum, which is obtained by multiplying the DFT coefficients by the corresponding filter gains [23]. These steps collectively produce the MFCCs, which are then used as input features for emotion classification. To further enhance the discriminative power of the extracted features, the Inverse Fourier Transform (IFT) is applied to the transformed Mel-frequency coefficients, resulting in a set of MFCCs, commonly referred to as static features. These coefficients capture the essential spectral characteristics of the signal.

D. Classification Method

Classification and pattern recognition are essential activities in data mining and machine learning. This paper used LR, KNN, RF, ANN, and SVM. In this work, all five classification models were used to detect emotion and classify it into seven categories: angry, happy, sad, neutral, surprised, fearful, and disgusted.

1) Artificial Neural Networks (ANN)

The Artificial Neural Networks model comprises three layers: an input layer for data, a hidden layer, and an output layer for the results of computations. The ANN is formed by connecting several nodes or neurons. The model comprises nodes that function as processing units. Weights denote connections between these nodes, mimicking the memory capacity of an artificial neural network. The way a neural network reacts is affected by the connection type, weight value, and excitation mode of different nodes [24]. ANN, on the other hand, is trained using a backpropagation algorithm, which is a supervised learning algorithm that resembles the workings of a human brain.

The basic model of an ANN is illustrated in Fig. 5. It operates like a nervous system comprising interconnected neurons, relaying information via forward connections.

The backpropagation algorithm reduces the discrepancies between network outputs and training input/output pairs [25].

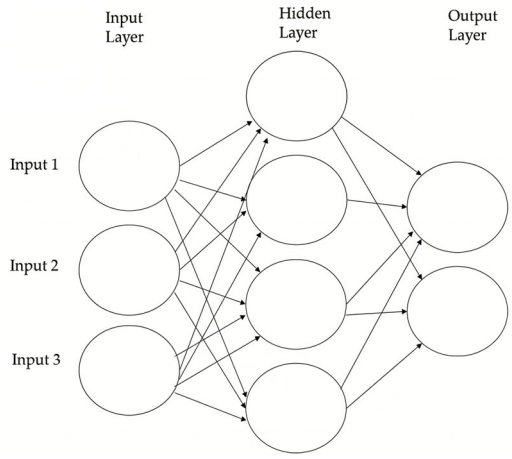


Fig. 5. Artificial neural network [26].

2) *Random Forest (RF)*

Random Forest is a robust classification and regression method that employs "bagging" or bootstrap aggregating. It forms an ensemble of trees by training each tree on two-thirds of the training set and evaluating its performance. This method ensures accuracy and stability by reducing model variance. This method constructs a group of classifiers using DT as described in Fig. 6. However, RF is a precision model that determines each T's unique error rate for classification by using DT to select a random data sample [27, 28]. Each DT is trained on a random sample with replacement from the original data, and the trained bootstrap samples of each DT are predicted to contain 37% duplicate occurrences. The other method of randomization is attribute sampling.

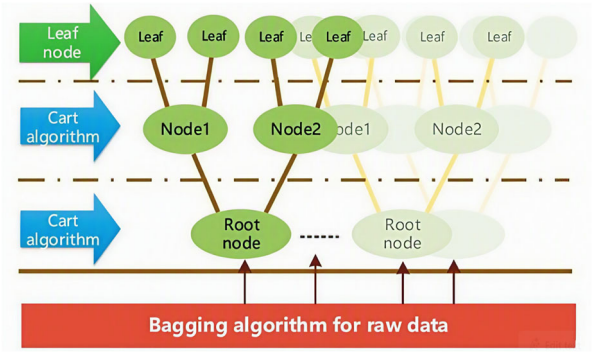


Fig. 6. Random forest structure [28].

The final prediction is determined by majority vote. The default RF configuration performs remarkably well and does not require parameter tuning. Additional tuning factors include creating leaf nodes, requiring a minimum sample size, and adjusting for tree depth. The RF method is a non-parametric supervised learning technique that combines many weak classifiers to achieve high accuracy and generalization performance through averaged outcomes using voting or mean-based methods. In Eq. (2), RF is the equal representation where the number of features used to identify comparable accounts is represented by N, with F_i being the value obtained from the system and Y_i is the original value used for feature i [29].

$$\mathrm{RF} = \frac{1}{N}\sum_{i=1}^{N}(F_i - Y_i)^2 \tag{2}$$

3) *Logistic Regression (LR)*

Logistic regression is a method used in binary classification that utilizes a logistic function to transform each input value into a probability. This strategy can quickly solve many classification issues. Multivariate linear regression is often used for continuous outcomes and is ideal for assessing multiple contributions and components simultaneously [30, 31]. Eq. (3) describes the logistic regression model:

$$\frac{\mathrm{Prob}(Y_i=1)}{\mathrm{Prob}(Y_i=0)} = \frac{P_i}{1-P_i} = e^{(\beta_0+\beta_1.X_1\ldots+\beta_k.X_k)} \tag{3}$$

where P_i represents the probability that Y_i equals 1, e edenotes the exponential constant, β_0, $\beta_1, \ldots \beta_k$ the regression coefficients (weights) assigned to each feature, $X_1, .., X_k$ the independent input features, and $(1 - P_i)$ signifies the probability that Y_i equals 0. It is also utilized as a statistical method to illustrate the connection between independent predictors and an outcome, especially in qualitative life research involving binary or dichotomous outcomes. However, LR is primarily an ordinal, multinomial, or binary model rather than a black box model. It predicts the probability of a response from the binary variable based on real-valued inputs. If the forecast is greater than 0.5, the outcome is classified as either 0 or 1. This method is very useful for binary response variables [32].

4) *K-Nearest Neighbors (KNN)*

K-nearest neighbors is a method that categorizes data items using several nearest neighbors. It is called a memory-based categorization method because it utilizes runtime training samples, which represent a lazy learning approach. The KNN process consists of two main operations: estimating the closest neighbors and determining the class associated with those neighbors. This method relies heavily on the training cases [33] for effective classification. KNN forecasts the condition of a set, drawing on the KNN of that set within the training data. It does not require training, but it struggles with selection. k values and computing distances and neighboring matches. The Sum of Errors (SSE) is obtained by calculating the common Euclidean distance between each cluster center and the point, as specified in Eq. (4) [34].

$$\mathrm{SSE} = \sum_{i=1}^{k}\sum_{x\in C_i}\mathrm{dist}^2\,(m_i, x) \tag{4}$$

here, k is the number of clusters, m_i is the cluster's center (mean), distance is the Euclidean distance, and x is a data point that belongs to a cluster C_i.

5) Support Vector Machine (SVM)

Support vector machines, which are a class of supervised learning models that utilize associated learning algorithms, are advanced classifiers used to analyze data for classification and regression analysis. SVMs serve the main purpose of demarcating decision boundaries (known as boundaries) to distinguish various classes in the dataset. The boundaries are designed to maximize the distance between them and the classes, which minimizes classification errors [35]. Essentially, the goal of SVMs is to maximize margin separation to improve classification accuracy. To be more specific, in machine learning, a learning algorithm uses a dataset that includes input data and their corresponding known responses (classes) to train a model. The aim is to allow the model to make reliable predictions regarding the behavior or outcome of new, previously unseen data [36]. Fig. 7 illustrates the schematic model of SVM.

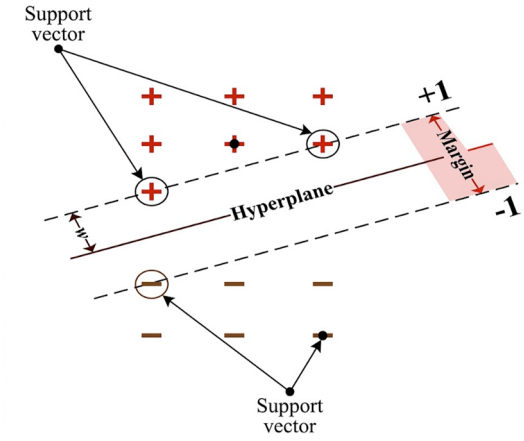


Fig. 7. The schematic model of SVM [37].

III. Results and Performance Evaluation

Examining how well the suggested model predicts is essential after the main model assumptions have been tested, trained, and proven correct. As a result, assessment metrics were used to evaluate the suggested models' applicability. As illustrated in Fig. 8, the confusion matrix is a helpful tool for assessing the effectiveness of classification and prediction algorithms [38]. It determines the percentages of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) in accuracy rate calculations [39, 40].

		Predicted Class	
		Positive	Negative
Actual Class	Positive	TP	FN
	Negative	FP	TN

Fig. 8. Confusion matrix [37].

The classification effectiveness of five models, LR, KNN, RF, ANN, and SVM, was compared using confusion matrices. Table I displays the confusion matrix for emotion detection with ANN. Table II illustrates the confusion matrix for RF, Table III presents the confusion matrix for the LR classifier, Table IV contains the confusion matrix for the KNN classifier, and Table V displays the confusion matrix for the SVM classifier.

The effectiveness of the proposed method was assessed in this study using various metrics, including accuracy, sensitivity, precision, specificity, F-measure, and MCC. These metrics are detailed in Eqs. (5)–(10), respectively [41, 42].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{8}$$

$$\text{F} - \text{measure} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{9}$$

$$\text{MCC} = \frac{\text{TP} \cdot \text{TN} - \text{FP} \cdot \text{FN}}{\sqrt{(\text{TP} + \text{FP}) \cdot (\text{TP} + \text{FN}) \cdot (\text{TN} + \text{FP}) \cdot (\text{TN} + \text{FN})}} \tag{10}$$

Table I: The ANN Confusion Matrix

Actual	Predicted							
	Angry	Disgusted	Fearful	Happy	Neutral	Sad	Surprised	Σ
Angry	446	2	0	1	0	1	1	451
Disgusted	0	446	1	1	0	2	1	451
Fearful	1	3	443	2	2	1	2	451
Happy	0	2	4	447	1	1	1	451
Neutral	1	4	4	2	443	1	0	451
Sad	0	4	1	0	0	447	1	451
Surprised	3	1	1	1	2	2	446	451
Σ	451	451	446	456	448	453	452	3157

TABLE II: THE RF CONFUSION MATRIX

Actual	Predicted							
	Angry	**Disgusted**	**Fearful**	**Happy**	**Neutral**	**Sad**	**Surprised**	**Σ**
Angry	450	0	0	0	0	0	1	451
Disgusted	1	450	0	0	0	0	0	451
Fearful	0	0	448	0	0	0	3	451
Happy	0	0	0	450	0	0	1	451
Neutral	0	0	0	1	450	0	0	451
Sad	0	0	0	0	0	449	2	451
Surprised	1	2	0	1	0	0	447	451
Σ	452	452	448	452	450	449	454	3157

TABLE III: THE LR CONFUSION MATRIX

Actual	Predicted							
	Angry	**Disgusted**	**Fearful**	**Happy**	**Neutral**	**Sad**	**Surprised**	**Σ**
Angry	304	21	38	14	30	33	11	451
Disgusted	15	381	13	10	8	19	5	451
Fearful	26	17	285	17	36	39	31	451
Happy	11	10	19	366	17	21	7	451
Neutral	23	11	27	24	314	40	12	451
Sad	41	17	42	17	52	270	12	451
Surprised	6	4	13	9	9	6	404	451
Σ	427	461	437	457	466	428	482	3157

TABLE IV: THE KNN CONFUSION MATRIX

Actual	Predicted							
	Angry	**Disgusted**	**Fearful**	**Happy**	**Neutral**	**Sad**	**Surprised**	**Σ**
Angry	451	0	0	0	0	0	0	451
Disgusted	29	422	0	0	0	0	0	451
Fearful	53	48	350	0	0	0	0	451
Happy	51	53	40	307	0	0	0	451
Neutral	56	48	67	66	214	0	0	451
Sad	72	55	67	64	56	137	0	451
Surprised	36	26	43	38	50	31	228	451
Σ	747	652	567	475	320	168	228	3157

TABLE V: THE SVM CONFUSION MATRIX

Actual	Predicted							
	Angry	**Disgusted**	**Fearful**	**Happy**	**Neutral**	**Sad**	**Surprised**	**Σ**
Angry	234	39	35	28	35	46	34	451
Disgusted	70	310	22	7	10	18	14	451
Fearful	91	41	168	15	29	48	59	451
Happy	55	34	40	255	23	19	25	451
Neutral	92	23	33	41	206	29	27	451
Sad	8	21	49	29	49	198	24	451
Surprised	76	4	14	5	12	3	337	451
Σ	699	472	361	380	364	361	520	3157

TABLE VI: PERFORMANCE EVALUATION OF ANN

Emotion	Accuracy	F1-Score	Precision	Sensitivity	MCC	Specificity
Angry	0.9968	0.9889	0.9889	0.9889	0.9870	0.9981
Disgusted	0.9968	0.9889	0.9889	0.9889	0.9870	0.9981
Fearful	0.9965	0.9877	0.9932	0.9822	0.9857	0.9988
Happy	0.9965	0.9877	0.9932	0.9822	0.9857	0.9988
Neutral	0.9958	0.9856	0.9802	0.9911	0.9832	0.9966
Sad	0.9958	0.9855	0.9888	0.9822	0.9831	0.9981
Surprised	0.9996	0.9878	0.9867	0.9889	0.9857	0.9977
Avg	**0.9964**	**0.9874**	**0.9886**	**0.9863**	**0.9854**	**0.9980**

TABLE VII: PERFORMANCE EVALUATION OF RF

Emotion	Accuracy	F1-Score	Precision	Sensitivity	MCC	Specificity
Angry	0.9999	0.9990	0.9955	0.9977	0.9961	0.9992
Disgusted	0.9999	0.9990	0.9955	0.9977	0.9961	0.9992
Fearful	1.0000	0.9990	1.0000	0.9933	0.9961	1.0000
Happy	0.9999	0.9990	0.995575	0.9977	0.9961	0.9992
Neutral	0.9999	0.9996	1.0000	0.9977	0.9987	1.0000
Sad	0.9999	0.9993	1.0000	0.9955	0.9974	1.0000
Surprised	0.9978	0.9965	0.9845	0.9911	0.9858	0.9974
avg	**0.9996**	**0.9988**	**0.9959**	**0.9958**	**0.9952**	**0.9993**

TABLE VIII: PERFORMANCE EVALUATION OF LR

Emotion	Accuracy	F1-Score	Precision	Sensitivity	MCC	Specificity
Angry	0.9147	0.693273	0.7136	0.6740	0.6441	0.9549
Disgusted	0.9528	0.836443	0.8282	0.8447	0.8089	0.9708
Fearful	0.8999	0.643341	0.6551	0.6319	0.5852	0.9445
Happy	0.9442	0.806167	0.8008	0.8115	0.7736	0.9663
Neutral	0.9087	0.686275	0.6745	0.6984	0.6330	0.9438
Sad	0.8923	0.614512	0.6287	0.6008	0.5521	0.9408
Surprised	0.9607	0.8669	0.8399	0.8957	0.8445	0.9715
Avg	**0.9247**	**0.7352**	**0.7344**	**0.736775**	**0.6916**	**0.9561**

TABLE IX: PERFORMANCE EVALUATION OF KNN

Emotion	Accuracy	F1-Score	Precision	Sensitivity	MCC	Specificity
Angry	0.9062	0.7529	0.6037	1.0000	0.7332	0.8906
Disgusted	0.9179	0.7651	0.6472	0.9356	0.7353	0.9150
Fearful	0.8992	0.6876	0.6172	0.7760	0.6343	0.9198
Happy	0.9011	0.6630	0.6463	0.6807	0.6054	0.9379
Neutral	0.8913	0.5551	0.6687	0.4745	0.5047	0.9608
Sad	0.8907	0.4426	0.8154	0.3037	0.455704	0.9885
Surprised	0.9293	0.6715	1.0000	0.5055	0.6834	1.0000
Avg	**0.9051**	**0.6483**	**0.7141**	**0.6680**	**0.6217**	**0.9446**

Tables VI to X show the detailed evaluation of each classification algorithm individually. It was noted that there was a discrepancy in the evaluation based on the type of emotion. For example, the LR algorithm was most accurate in detecting the emotion "Fearful" with a score of 100% and least accurate in detecting the emotion "Surprised" with a score of 99.78%, while the ANN algorithm's accuracy ranged between 99.96% for the emotion "Surprised" and 99.58% for the emotions "Neutral" and "Sad". On the other hand, the accuracy of the LR ranged between 89.23% and 96.07%. As for the KNN, the accuracy ranged between 89.07% for the emotion "Sad" and 92.93% for "Surprised". The worst performance was for the SVM, with accuracy ranging between 78.39% and 90.59%.

Table XI presents the average values for all performance metrics across all classifiers and emotions. This confirms that the proposed system achieved smooth and responsive performance in emotion detection and identified basic emotions according to seven categories: surprise, anger, sadness, neutral, fear, disgust, and happiness. The accuracy of emotion detection varied from 86.88% with SVM to 99.96% with RF. On the other hand, the highest F-measure record was 99.88% for RF, and the lowest was 54.19% for SVM. As for MCC, it ranged from 99.52% for RF to 47.02% for SVM. These results indicate that the RF model surpasses all classifiers in performance, while ANN comes in second, with an accuracy difference of less than 0.32%. LR follows with an accuracy of 92.47%, and KNN 90.51%, while SVM performs the worst, with an accuracy of 86.88%.

TABLE X: PERFORMANCE EVALUATION OF SVM

Emotion	Accuracy	F1-Score	Precision	Sensitivity	MCC	Specificity
Angry	0.7839	0.4069	0.3347	0.5188	0.2924	0.8281
Disgusted	0.9040	0.6717	0.6567	0.6873	0.6157	0.9401
Fearful	0.8492	0.4137	0.4653	0.3725	0.3311	0.9286
Happy	0.8983	0.6137	0.6710	0.5654	0.5583	0.9538
Neutral	0.8723	0.5055	0.5659	0.4567	0.4364	0.9416
Sad	0.8682	0.4876	0.5484	0.4390	0.4165	0.9397
Surprised	0.9059	0.6941	0.6480	0.7472	0.6411	0.9323
Avg	**0.8688**	**0.5419**	**0.5557**	**0.5410**	**0.4702**	**0.9235**

TABLE XI: AVERAGE PERFORMANCE METRICS OF THE SUGGESTED MODEL

Classifier	Accuracy	F1-Score	Precision	Sensitivity	MCC	Specificity
RF	0.9996	0.9988	0.9959	0.9958	0.9952	0.9993
ANN	0.9964	0.9874	0.9886	0.9863	0.9854	0.9980
LR	0.9247	0.7352	0.7344	0.7367	0.6916	0.9561
KNN	0.9051	0.6483	0.7141	0.6680	0.6217	0.9446
SVM	0.8688	0.5419	0.5557	0.5410	0.4702	0.9235

IV. DISCUSSION

Emotion detection is a rapidly evolving field with significant implications across various domains, particularly in public safety, healthcare, and human-computer interaction. Leveraging artificial intelligence and image processing techniques, recent studies have explored a wide range of machine learning models for automatic emotion recognition. Deep learning and machine learning have proven especially effective due to their ability to automatically detect and classify complex patterns in visual data. These models primarily focus on

object detection and classification, making them well-suited for facial emotion analysis.

This study proposes a novel emotion detection framework that integrates MFCC feature extraction with five classification algorithms: LR, KNN, RF, ANN, and SVM. The changes in intensities and the spatial pattern of the resulting signals keep the crucial facial expression information even though the dimension of the image is reduced from 2D to 1D. The MFCCs encode the spectral features of these patterns, yielding a compact representation of expression-related information.

This results in distinguishable spectral signatures for different emotions that the classifiers can learn well. This shows that MFCC-based representations are still highly informative for image-based emotion recognition.

The performance of the proposed system is benchmarked against existing models in the literature, as summarized in Table XII. The results demonstrate that the proposed model achieves superior accuracy, with RF and ANN reaching 99.96% and 99.64%, respectively, outperforming several established methods. For example, traditional approaches using HOG and SVM reported accuracies between 89% and 96% [4, 5], and [15], while CNN-based models varied from 73% to 98.48% [7, 8, 11, 14], and [18]. More recent architectures, such as YOLOv5 and ResNet50 with CBAM, achieved accuracies of 97.08% [12, 13], GB reached 99% [16]. Compared to these, the proposed MFCC-based system demonstrates competitive and often superior performance, validating its effectiveness for real-time emotion recognition.

TABLE XII: BENCHMARKING WITH LITERATURE

Study/Year	Methods	Accuracy
[4]/2025	HOG and SVM	96%
[5]/2020	HOG and SVM	89%
[6]/2023	VGG-19, and Xception	98.4%
[7]/2026	2D-CNN	98.48%
[8]/2024	CNN	96%
[11]2022	CNN	98%
[12]/2023	YOLOv5	99%
[13]/2025	ResNet50, TCNs, CBAM	97.08%
[14]/2026	CNN	85.47%
[15]/2022	HOG and SVM	96.88%
[16]/2022	GB	99%
[17]/2022	DFCNHP	98%.
[18]/2021	CNN	73%
Proposed	**MFCC, LR, KNN, RF, ANN, and SVM**	**99.96%**

V. CONCLUSION

This study presents a comparative analysis of various machine learning algorithms for emotion detection using facial recognition techniques. The proposed system integrates image preprocessing with MFCC feature extraction to classify seven fundamental emotions: happiness, anger, sadness, surprise, neutrality, fear, and disgust. Five classification models, LR, KNN, RF, ANN, and SVM, were evaluated using a dataset of 3157 labeled images. The system's performance was assessed using multiple metrics, including accuracy, MCC, F1-Score, specificity, recall, and precision. Experimental results demonstrate that RF and ANN significantly outperformed the other models, achieving accuracy of 99.96% and 99.64%, respectively. LR followed with an accuracy of 92.47%, while KNN and SVM yielded the lowest performance, with accuracy of 90.51% and 86.88%, respectively. These findings highlight the effectiveness of proposed approaches, particularly ANN and RF, in real-time emotion recognition tasks.

VI. LIMITATIONS AND FUTURE IMPROVEMENTS

Despite the high accuracy achieved by the proposed emotion detection system, especially when employing the RF and ANN models, several limitations should be acknowledged. First, the dataset used in this study included only seven basic emotions and did not capture the more complex, subtle, or mixed emotional states that are common in natural human interactions. This restricts the system's ability to generalize to real-world scenarios. Furthermore, the evaluation was conducted exclusively on still images; therefore, the system's performance in real-time video-based emotion recognition, where temporal dynamics, micro-expressions, and motion cues play a critical role, remains unexamined. Finally, potential biases within the dataset, such as uneven class distribution or the presence of exaggerated, posed facial expressions, may have contributed to the high accuracy scores. These limitations highlight the need for larger, more diverse, and more representative datasets in future research to enhance the system's robustness and applicability.

DATA AVAILABILITY STATEMENT

The dataset used in this study is publicly available. Facial emotion data were obtained from the FER-2013 dataset introduced by Goodfellow *et al.* and can be accessed through publicly available repositories.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

Muneera Altayeb was responsible for project administration, design, and development of the proposed model. Muneera Altayeb and Sanaa Salama supervised the testing and implementation of the model, while Sanaa Salama prepared the necessary materials, collected and analyzed the data, and performed the simulations. Muneera Altayeb wrote the initial draft of the research paper, which was then reviewed and edited by Muneera Altayeb and Sanaa Salama. All authors provided feedback on previous drafts. All authors reviewed and approved the final version of the paper.

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