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ROLE OF FACE FEATURE CLASSIFICATION FOR THE DETECTION AND RECOGNITION

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Abstract
Humans easily recognize emotions from facial expressions, while computers struggle with it. Emotion recognition from facial expressions is vital for human-computer interaction, using machine learning in most studies. Computer vision research on simple emotion recognition remains difficult. Surprise, sadness, fear, contempt, happiness, & anger are among examples. Recently, deep learning has been discussed as a possible answer to several practical problems, one of which is recognition of emotion. In this paper, we enhance the CNN (Convolutional Neural Network) method for distinguishing seven basic emotions and tested the effects of various preprocessing procedures on classification accuracy. Through the application of facial traits and emotions, this research aims to improve emotion recognition. Computers draw more accurate inferences about a person's mental state and provide more appropriately customised replies if they can recognise or elicit facial expressions that suggest such states. Therefore, we investigate whether a deep learning approach employing a MCNN (Modified Convolutional Neural Network) may enhance emotion recognition from facial data. After the input image has been cleaned of noise using the preprocessing method and features have been extracted during the pretraining phase, face detection may be performed with high accuracy. 7 emotions represented by the FACS (Facial Action Coding System) are the basis for the MCNN we propose for classifying different facial expressions. To classify facial features, our proposed MCNN attained an impressive 97.1% accuracy.

Keywords: *Classifying, face features, Recognition, Detection*

1. Introduction

Classifying face features is a crucial step in improving emotion recognition and detection systems. By analyzing various facial components like eyes, eyebrows, mouth, nose, and their subtle changes, these systems can identify specific emotional expressions more accurately [1]. Advanced machine learning algorithms, like deep neural networks, can be employed to extract and process these features effectively. By understanding and categorizing facial cues associated with different emotions, the system can provide more nuanced and precise emotion recognition, enabling applications in areas like human-computer interaction, virtual reality, and emotional well-being assessments.

Emotion recognition is a skill that is both highly sought after and extremely difficult to master. The measurement of stress and blood pressure are just two examples of the various uses for emotion recognition [2]. Emotional facial features include the expressions of happiness, sadness, calmness, and neutrality. Numerous methods and algorithms aid in the detection of the inner workings of the human body [3]. Additionally, ongoing research and development in this area could improve the effectiveness and dependability of emotion recognition and detection systems, leading to the creation of more advanced and sympathetic AI technologies [4].[5].

Instantaneous thought detection is possible with emotion recognition [6]. Simply by employing emotional recognition to identify ailments early, It protects the body from dangerous pathogens [7] and diseases [8]. Emotion recognition has the primary advantage of allowing us to infer people's mindsets without having to directly question them [9].

Without prior knowledge of the assessor's skill, face recognition is crucial for video-based evaluation of a wide range of emotions [10]. In this research, we present two approaches for computing the video-based facial recognition algorithm, including one that uses precise calculations of angles & distances. Another is arranging all video clips in a way that reduces the number of key snapshots.

Automatic facial expressions have potential applications in multimodal human-computer interaction, intelligent settings, pain evaluation, neurology, fraud detection, psychiatry, and clinical psychology [11]. The FACS is used in facial expression analysis [12] for the purposes of action unit identification and feature extraction. The two primary approaches are appearance-based & geometry-based feature extraction. The latter are points that represent individual facial features and are used to create feature vectors that mathematically represent the face. The latter is implemented using techniques like Gabor Wavelets for feature vector extraction from either a narrowly or broadly defined portion of a facial image. Emotional recognition and facial expression analysis are two areas where deep learning has demonstrated promising results. The effectiveness, however, is data volume dependent. The efficiency improves with a greater quantity of data. Unfortunately, deep learning cannot be used to facial expression datasets at this time due to their small sizes. Many researches employ preprocessing augmentation strategies including cropping, scaling, translating, and mirroring to increase data variance and volume. These preprocessing methods are great for increasing the efficiency of deep learning. The study use deep learning to create such a distinction, with the overarching goal of drawing attention to the importance of data preparation in maximising deep learning's efficacy. Before looking at the spread in accuracy, we first assess the precision of each preprocessing method on its own.

By increasing the size of the training set through an image augmentation-based data collecting technique, deep learning strategies can aid in the reduction of this image's dimensional space [13]. Images with rough edges can be softened with the use of kernel filters. The accurate prediction of facial expressions of sadness and stress is now possible with ML techniques. PPG [15] & ECG

[14] improved findings for the identification of negative emotions like sadness and anger when paired with the 28 variables obtained using machine learning techniques.

Looking at a person's facial expressions is the next best thing to actually talking to them to figure out how they're feeling. Some articles build databases covering the years 2010–2022, incorporating the vast majority of feature extraction and classification, to improve classification accuracy and produce better results using SVM (Support vector machine) approach & DL method. Principal Component Analysis (PCA) and Local Binary Pattern (LBP) [18] are two useful methods of evaluation. FACS (Facial Acting Coding System), which was established in this study to recognise all potentially apparent anatomically based face motions, was initially developed. By enhancing FACS with deep learning techniques, the proposed paper broadens the application range of emotion recognition. The accurate classification of seven emotions through MCNN can have practical implications in many fields like human-computer interaction, affective computing, virtual reality, & psychology.

Overall, the paper's contributions lie for development of an optimized emotion recognition system that builds upon established FACS system while leveraging deep learning to achieve superior accuracy. The exploration of various feature extraction techniques further enhances the system's robustness and potential applicability in diverse real-world scenarios.

1.1 Contributions

The proposed paper makes several novel contributions in Facial Emotion Recognition (FER) using a deep learning algorithm and leveraging the FACS (Facial Acting Coding System). These novel contributions are summarized as:

1. The paper introduces a novel emotion recognition model called MCNN (Modified Convolutional Neural Network) based on facial expressions, improving accuracy over existing techniques.
2. We combine FACS with deep learning for enhanced facial expression classification.
3. We explore diverse feature extraction approaches for FER.
4. We demonstrate MCNN outperforming traditional methods, leveraging advanced deep learning algorithms.

2. Literature Review

Babajee et al. [16] developed a system to deduce human emotions from facial expression using DL algorithm. The authors used deep learning and CNN to create a system that can identify seven different emotions simply by looking at a person's face. They used a dataset of 32,398 people to collect data on emotion recognition using FACS. The identification approach must be unsuccessful as an optimisation strategy.

Using deep neural networks and machine learning methods, Hassouneh et al. [17] created real-time FER that relies on EEG & facial expressions. They used digital markers and optical flow to identify people by their faces. Due to its acknowledged reduced computer complexity, the optical flow algorithm methodology is used to facilitate physical obstacles for humans.

Tan et al. [18] used neuro-sense and a spiking neural network model of spatio-temporal EEG signals to create a short-term emotion identifier and comprehender. They used the SNN method. It shed light on how the mind functions. One of the methods used to quantify the EEG data is the arousal-valence space. The four quadrants of the arousal-valence diagram are high arousal, low arousal, high valence, and low valence.

Using deep learning and the cloud, Satyanarayana et al. [19] created a system for recognising emotions. One of the most useful methods in many contexts is facial emotion recognition. When it comes to identifying people, the deep learning algorithm is important. They compiled responses spanning a wide range of human emotions, from grief and delight to calm and rage. Because of this, the python code processes the data and assigns a unique IP address to each method.

Jayanthi et al. [20] built a framework that uses speech and static images to classify emotions by fusing deep classifiers. One of the most important tools for determining a person's stress level is the ability to recognise their emotions. Emotion recognition and speech modulation are two characteristics that play an important part in determining a person's stress levels. In order to determine the stress, they devised an integral framework that took the form of a static function and incorporated both emotional recognition and speech modulations. As a result, their solution was more precise than that of competing algorithms.

Li et al. [21] implemented a survey of deep facial expression recognition. One of the trickiest parts of the network system is emotion recognition. Neither sufficient nor comparable training sets exist, which is FER's primary problem. In the first scenario, the dataset is presented in a manner consistent with the distribution selected by the neural pipeline method. It helped with some of the problems that come with using the FER approach.

Facial microexpression detection was achieved by Yadahalli et al. [22] via a deep learning approach. The six emotions (happy, sad, furious, afraid, neutral, and startled) were utilised to collect the eight data points that make up the dataset. Since the FER model was already present in the amassed dataset, they simply merged it with CNN to improve accuracy.

Asaju et al. [23] tackled the difficulty of accurately classifying facial expressions by taking a temporal approach. These techniques for human emotion recognition were developed using a CNN and DL method. Feature extraction is performed using the VGG-19 procedures. After that, we employ the BiL-STM architecture and a precise mapping method to recognise human emotions. Classifications made with the aid of a deep learning neural network are evaluated for quality and accuracy using the CNN- BiL-STM method. Emotions on people's faces have been categorised as joyful, sad, furious, or neutral thanks to the “DISFA (Denver Intensity of Spontaneous Facial Action) dataset”. Since then, scientists have mined the “DAiSEE (Dataset for the Effective State in the E-Environment)” for indicators of mental distress.

When it came to facial expression recognition, face detection, and general face recognition, Sati et al. [24] relied on NVIDIA. Jetson Nano was able to get better accuracy and classification results in the difficult work of traditional and modern facial expression identifications by incorporating extra variables into this procedure. The ANN method is useful for interpreting emotional emotions.

Using the maximal boosted CNN and LSTM, Rajan et al. [25] built a novel deep learning model for facial expression recognition, and they also provided a slightly different model using the boosted FER approach, both of which are meant to lessen spaces of dimensions & impact of input function noises. After that, we use the dual CNN method, and things become even better. In this paper, we show that the LSTM and MBCNN may work together to generate reliable outcomes from feature extraction and classification tasks.

Domnich et al. [26] collected the SASE- FE dataset according to gender, performed gender bias evaluation in emotional recognition based AI technique. Three male and three female neural networks are then created from the dataset. The process includes a training & testing phase. The final product will be split into three groups according to factors like the scope of the project, the gender of the participants, and the type of information being gathered.

Ekundayo et al. [27] built a multilabel convolution neural network for the aim of FER & ordinal intensity estimate. The multi-label CNN used in the research was put into action. Different cultures may react very differently to the same occurrences due to the fact that there are multiple ways to classify emotions. ML-CNN incorporated the BEC (Binary Cross Entropy) losses. A chain classifier was utilised for classification, while the Multilabel Kernel Nearest Neighbour and MLARAM were constructed with the VGG-16 for usage in feature extraction.

Wang et al. [28] implemented a state-of-the-art deep learning technique for this research. In this research, we applied the deep learning four-class model. Convolutional neural networks and other deep architectures make up the first category. The neural networks are profoundly affected by the deep learning paradigm. Machine learning algorithms rely heavily on it. Importantly, the categorization makes use of both linear and nonlinear features, both of which contribute greatly to the accuracy of the data. The filter's sensitivity to noise and the number of dimensions can be reduced with the use of a convolution layer, the first filter layer. Over-fitting is reduced thanks to the CNN's pooling layer. As a result, the dysfunctional data was taken out of the function.

3. Proposed Methodology

CNN (Convolutional Neural Network) is the technique for image analysis that is most frequently employed contrary to a MLP (Multilayer Perceptron). The proposed method adopts a two-tiered

CNN architecture. Initially, the image's background is removed to facilitate subject identification and emotion elicitation. The main expressional vector (EV) is derived either through a standard CNN network module or by pinpointing expressive areas on the face. Changes in the EV correspond closely to shifts in expression. To obtain the EV, a simple perceptron unit is applied to a foreground-only facial image. Notably, the final stage of the FERC model incorporates a nonconvolutional perceptron layer. Each convolutional layer in the deep neural network processes input data by applying convolution, allowing for pattern discovery. The first-part CNN, responsible for backdrop removal, utilizes filters such as edge, circle, and corner detectors, which capture various forms: objects, textures, and edges in input images.

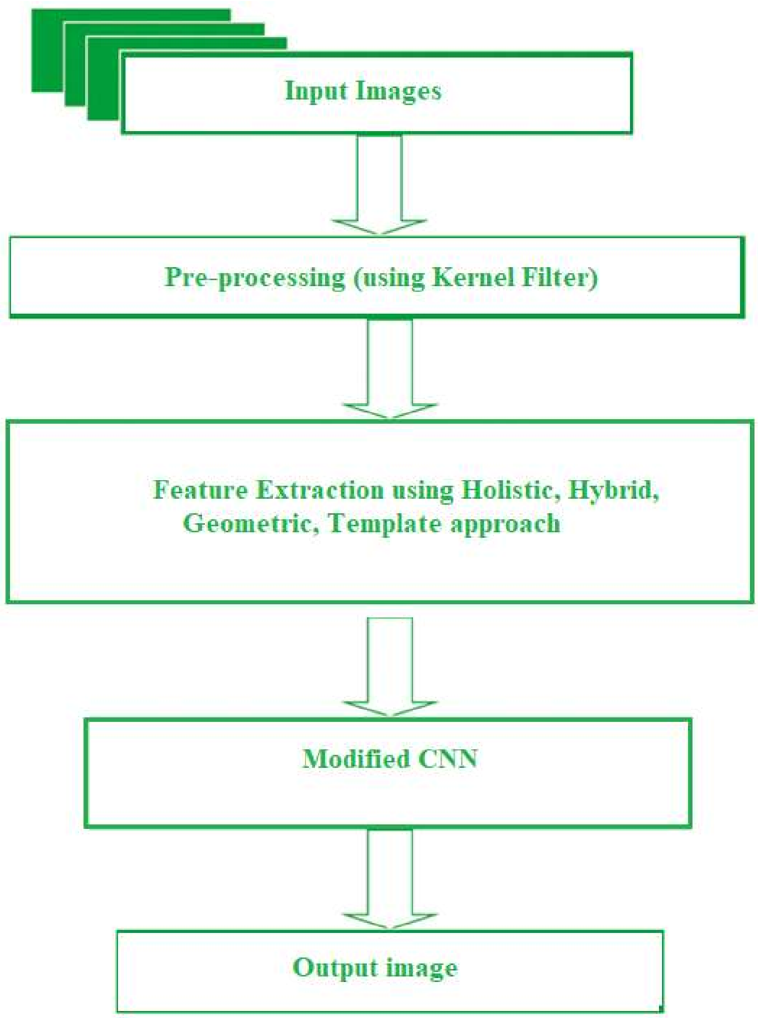

Fig 1: Workflow of proposed MCNN approach

The second component of the CNN filter detects specific facial features like eyes, ears, lips, nose, and cheeks. To reduce dimensionality constraints, kernel filters are employed in this study. The feature extraction process, including holistic, hybrid, geometric, and template-based strategies, is then conducted after preprocessing. Finally, the Modified CNN model of facial expression is obtained through this feature extraction procedure, enabling continuous output.

An overview of the proposed method shows that it involves preprocessing of the input image. The image noise is diminished with the help of the preprocessing method. Figure 1 provides an abstract of the proposed MCNN.

3.1. Steps

Fig. 2 shows the proposed architecture. The dataset includes different facial expressions, and the preprocessing method is used to this input.

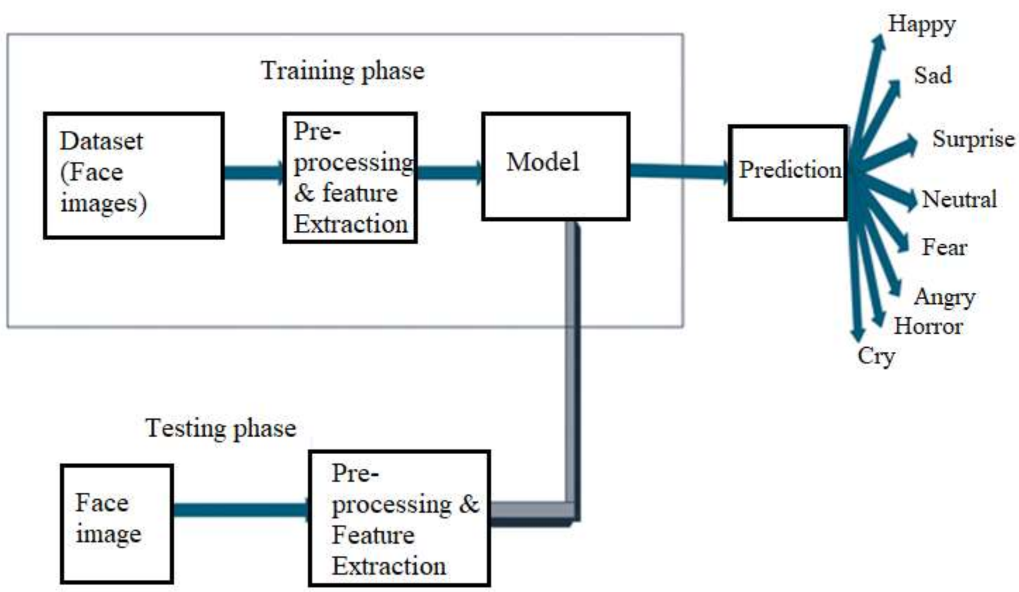

Fig 2: Architecture of proposed method

3.2. Preprocessing

In this work, the kernel filter is a crucial element for facial recognition, serving multiple purposes such as reducing dimensionality, smoothing edges, and decreasing image blurriness. The implementation of the kernel filter for image preprocessing is carried out.

Edge detection, a significant kernel filter technique, plays a vital role in predicting accurate edges and reducing dimensional space. The smoothing kernel comprises distinct filter evaluations: the median, Gaussian, average, and box filters.

The objectives of pre-processing method includes: applying noise-reduction filter & converting RGB images to grayscale.

$$(f * g)(a,b) = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} f(j,j)(g(a-i,b-j) \qquad (1)$$

The edge detection kernels consist of three different operators: Laplacian operator, Sobel operator, & Prewitt operator. These operators are applied to the input data using the convolution method. After measuring the error level, the appropriate filter is chosen to eliminate specific faults. The smoothening kernel is particularly effective in reducing noise from input images.

The "Gaussian filter" serves as a low-pass filter, and it is especially useful for removing Gaussian noise from input images. Additionally, Gaussian noise filter eliminates blurring scales from photographs, accurately predicting the focal points in an image.

$$G(u,v) = \frac{1}{2 * 3.14 * \phi^2} e^{\frac{-(u^2+v^2)}{\psi^2}} \qquad (2)$$

The kernel filter's Gaussian mathematical expressions are displayed in Eqn (2). The median filter, one noise-removal filter, enhances the input image with salt and pepper to assist minimise noise.

3.3. Feature Extraction

In image processing, feature extraction plays a crucial role as one of the fundamental methods. The initial step in face recognition is face detection, which involves identifying the presence of a face in the input image. Once the face is detected, the subsequent step is face extraction, where the specific facial features are isolated. Feature extraction allows for the categorization and verification of the image's authenticity.

Upon completing the feature recognition process, feature extraction minimize dimensionalities of input images and their corresponding edges. The identification of an image is accomplished through recognition and analysis of its distinctive features.

The forms of feature recognition implemented in this paper are Holistic & Hybrid approach

3.3.1. Holistic Approach

Among the crucial approaches in facial recognition is the holistic methodology, which involves recognizing the entire face in the input image. This comprehensive analysis makes it easier to identify various emotions displayed on the face, including sobbing, rage, sadness, and happiness. As a result of its effectiveness, the holistic method finds wide application, exemplified in Eigen and Fisher faces [26].

3.3.2. Hybrid Approach

The facial image recognition demonstrates high accuracy, in identifying expressions of mouth, nose & eyes. In facial recognition, the hybrid feature extraction combines both hybrid and all-image features to achieve its objectives.
This method employs several strategies of facial expression forms: They are given as follows:

3.3.2.1 Geometric-based technique

In this procedure, the image's size and placement in relation to other objects are considered. Geometric-based feature extraction is employed to correct edge detection and enhance the image's shape. The canny filter is a common choice which undergoes ‘gradient analysis’ & yields clever filter outcomes. Typically, the “canny filter” is utilized for image edge recognition, and prior to its application, the Gaussian filter is used to detect and reduce noise.

After identifying potential edges using a smoothing threshold, the gradient magnitude aids in image smoothing. The recognition of an extracted feature, such as the extraction of local features such as the nose, brows, eyes and mouth, is the definition of a geometric feature. The geometric feature technique in the geometric-based approach, as shown in Fig. 3, takes care of the size and relative placement by using the gradient magnitude and the output of the canny filter.

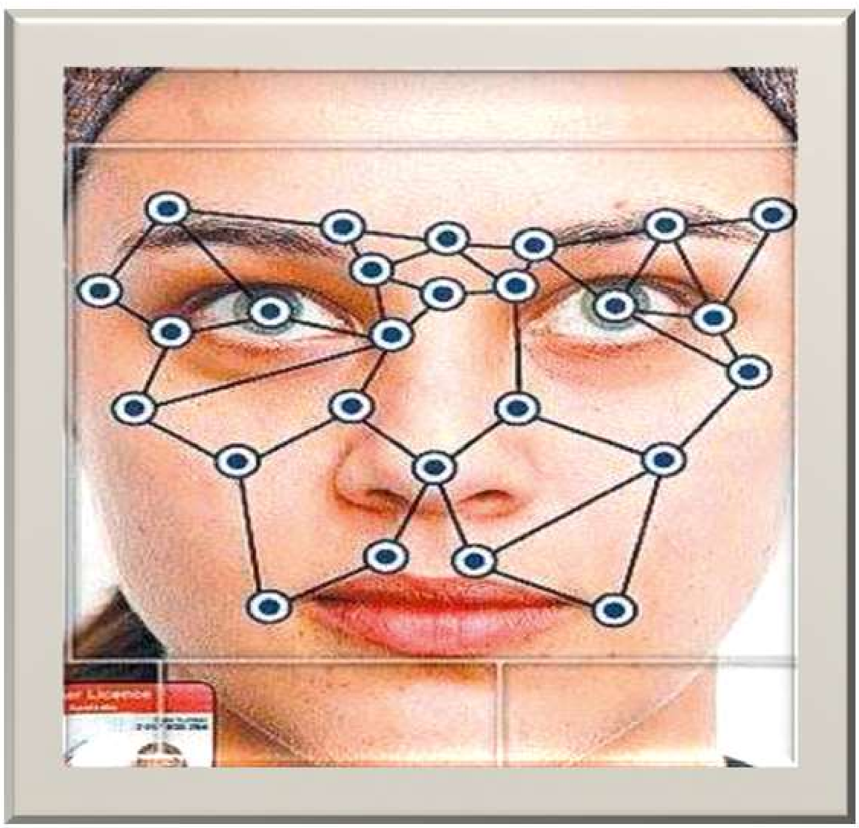

Fig 3: Geometric-based technique

3.3.2.2 Appearance-based approach

Using feature extraction, the appearance-based method is based on the PCA [42]. The basic goal of PCA is to reduce images' tremendous dimensionality into compact, dimensionality-independent images. The image's outcome is faultless.

3.3.2.3. Colour Based Technique

The RGB (Red, Green, and Blue) colours are the primary emphasis of the color-based technique. As the first stage of the preprocessing procedure, the RGB image is converted to a grayscale image. As a result, the binary picture is created from the grayscale image using the useful threshold settings. Therefore, all procedures to eliminate the calculated color-saturated value have been finished. This method is modified by including some features, such as the threshold function, to determine the saturated value.

The noise was discovered after the threshold applied to the image had finished working. Then several closed & open functions, including the mouth, eyes, & ears. This procedure managed the extractions, as well as several facial functions. By utilising the image's threshold function, Fig. 4 implements the numerous skin map types from the original image. This image with features extracted provides the input for the suggested MCNN when deep learning is used.

Fig 4 : The original image with different skin mappings

3.4 Convolutional Neural Network

Convolutional neural networks (CNN) are among the deep learning algorithms. The CNN technique is nothing more than an essential layer network.

According to Fig. 5, the CNN employs a classification technique to carry out the particular multilayer task. The RELU (Rectified Linear Unit) layer with convolution is used by CNN to process input images before sending them to the maxpooling algorithm. The output image is passed across the completely linked layer because this process is repeated just once. It aids in separating the precise output. The completely connected layer aids in classifying the picture as well.

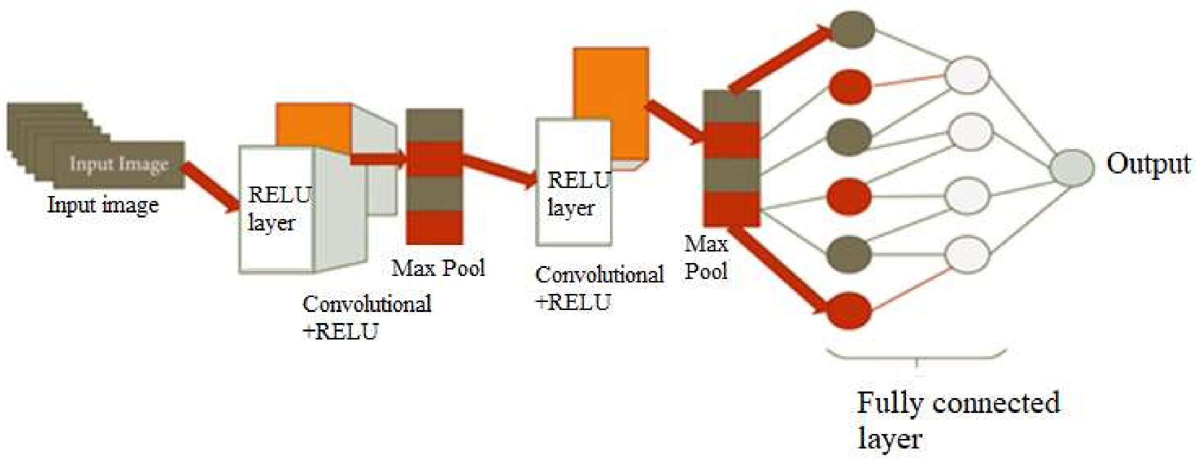

Fig 5: CNN

In the CNN architecture, the RELU function is responsible for the layering process. The convolutional layer is commonly employed for image classification, and the CNN's RELU function aids in effectively distinguishing various facial expressions. After the data is processed, it undergoes maximum pooling, a technique that plays a pivotal role in enhancing data analysis, mitigating overfitting, and reducing the dimensionality of images. The completely linked layer passes the results. The classifying layer is another name for this layer.

3.4.1 Proposed MCNN

In this paper, we propose Modified CNN. We modify the CNN architecture to improve the CNN for better recognition accuracy to classify face features. Layers are modified and given as follows:

(1) Convolutional Layer: The input image goes through the Convolutional Layer, where multiple filters are applied to detect different patterns and features within the image.

(2) Activation Function (RELU): After the Convolutional Layer, The output undergoes the ReLU activation function, introducing non-linearity to the network.

(3) Pooling Layer (Max pooling): The output from the ReLU layer then goes through the Maxpooling technique, which helps to reduce the spatial dimensions of the data while retaining the important features. Maxpooling selects the maximum value from a group of pixels, further reducing the computational load.

(4) **Repeat Layers:** The process of applying Convolution, ReLU, and Maxpooling can be repeated multiple times (typically, you stack several convolutional blocks) to capture more abstract features at different levels of the image.

(5) **Fully Connected Layer:** The output is flattened and then sent through one or more fully connected layers following numerous convolutional layers. Each neuron in these layers is connected to every neuron in the layer below it, as is normal for dense layers.

(6) **Output Layer:** The final fully connected layer produces the output for classification. The choice of activation functions and the number of neurons in the output layer depend on the specific task, with the number of neurons typically corresponding to the number of predicting classes.

Based on this, we create a modified CNN architecture, shown in Fig 6.

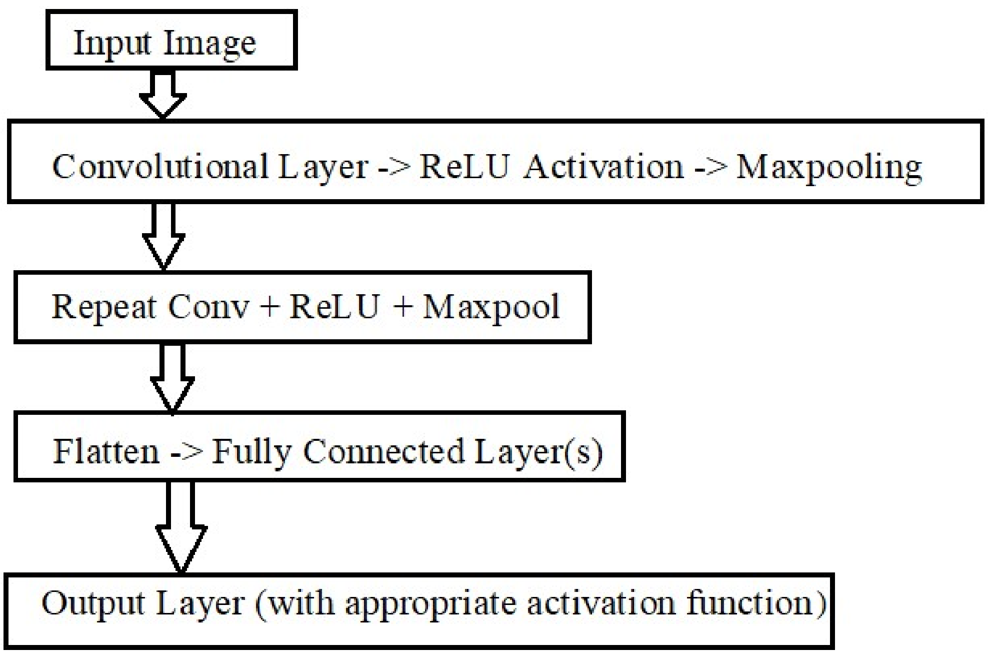

Fig 6: Proposed MCNN architecture

The task compexity and the dataset affects the number of layers, the number of neurons in each layer, and whether dropout or regularisation is used.
We finally implement Proposed MCNN algorithm in actual implementations based on our chosen deep learning framework “TensorFlow“ and the specific CNN architecture we propose is shown in algorithm 1 using Python code.

Algorithm 1: Pseudocode for MCNN Classification Algorithm for Face Feature Recognition and Detection

1	# Define constants for emotion codes
	HAPPY = 0
	SAD = 1
	SURPRISE = 2
	NEUTRAL = 3
	FEAR = 4
	ANGRY = 5
	HORROR = 6
	CRY = 7

2	# Define a function to extract face features using Modified CNN
	function extract_face_features(image):
	  # Preprocess the input image (resizing, normalization, etc.)
	  preprocessed_image = preprocess(image)
	
	  # Convolutional Layer 1: Edge, Circle, and Corner detection
	  conv1_output = apply_convolutional_layer(preprocessed_image, edge_filter, circle_filter, corner_filter)
	
	  # MaxPooling Layer 1: Reduce spatial dimensions
	  pooled1_output = max_pooling(conv1_output)
	
	  # Convolutional Layer 2: Additional filtering and face identification
	  conv2_output = apply_convolutional_layer(pooled1_output, median_filter, gaussian_noise_filter, face_detection_filter)
	
	  # MaxPooling Layer 2: Reduce spatial dimensions
	  pooled2_output = max_pooling(conv2_output)
	
	  # Feature Extraction: Holistic, Hybrid, Geometric, Template-based techniques
	  features = feature_extraction(pooled2_output)
	
	  return features

3	# Define a function to train the Modified CNN model for emotion classification
	function train_emotion_classifier(features, labels):
	  # Split the dataset into training and validation sets
	  train_features, train_labels, val_features, val_labels = split_dataset(features, labels)

	# Create the Modified CNN model for emotion classification
	model = create_modified_cnn_model()
	
	# Train the model using the training data
	train_model(model, train_features, train_labels)
	
	# Evaluate the model using the validation data
	accuracy = evaluate_model(model, val_features, val_labels)
	
	return model, accuracy

4	# Main function for emotion recognition and detection using Modified CNN
	function main():
	# Load the dataset containing face images and corresponding emotion labels
	dataset = load_dataset()
	images = dataset['images']
	emotion_labels = dataset['emotion_labels']
	
	# Initialize lists to store extracted features and corresponding labels
	extracted_features = []
	extracted_labels = []
	
	# Extract face features for each image in the dataset
	for image, label in zip(images, emotion_labels):
	features = extract_face_features(image)
	extracted_features.append(features)
	extracted_labels.append(label)
	
	# Convert the extracted features and labels to numpy arrays
	extracted_features = np.array(extracted_features)
	extracted_labels = np.array(extracted_labels)
	
	# Train the emotion classifier using the extracted features and labels
	trained_model, accuracy = train_emotion_classifier(extracted_features, extracted_labels)
	
	# Save the trained model for future use
	save_model(trained_model, 'emotion_classifier_model')
	
	print("Training completed. Accuracy:", accuracy)

```
# Run the main function
main()
```

4. Results and Discussions

4.1 Dataset

The dataset includes about 32,298 images with individual labels. We chose the FER2013 (Facial Expression Recognition 2013) dataset for further research because the images are 4848 pixels in size. The dataset is made up of two columns: one for pixels and one for emotions [29]. Table 1 presents the FER2013 dataset used for categorizing emotions through feature extraction. The pixel column displays the pixel values, while emotional actions are interpreted using a code value ranging from 0 to 6.

Table 1: Dataset for emotion classification

Code	**Emotions**
0	Happy
1	Sad
3	Surprise
4	Neutral
5	Fear
6	Horror
7	Cry

4.2 Metrics

(1) **Clarity**: Clarity is a performance indicator for binary classification models that is determined as the ratio of Real Positives to the sum of Real Positives and False Positives.

$$Clarity = \frac{RP}{RP + FP} \quad (3)$$

(2) Accuracy: Accuracy is a measure used to evaluate a binary classification model's overall performance and it is calculated as the ratio of the sum of Real Positives (RP) and Real Negatives (RN) to the total number of instances (RP + RN + FP + FN).

$$Accuracy = \frac{RP + RN}{RP + RN + FP + FN} \quad (4)$$

RP (Real Positive): A result or prediction that correctly identify a positive instance as positive in a binary classification problem.

RN (Real Negative): A result or prediction that correctly identify a negative instance as negative in a binary classification problem.

FP (False Positive): A result or prediction that incorrectly identify a negative instance as positive in a binary classification problem.

FN (False Negative): A result or prediction that incorrectly identiy a positive instance as negative in a binary classification problem.

4.3 Training & Testing Model

During the training stages, 80% of the data serves as input, and preprocessing is applied to reduce noise in the filter. Feature extraction is then employed to tackle the high dimensionality of the filter space. Our proposed method explores various feature extraction strategies, enabling edge detection and generating output images with appropriate size and clarity. Both categorization and feature extraction are carried out simultaneously on the data.

In the classification phase, features from both the training and testing data are transferred, resulting in three models for analysis from the training iterations $20, 200\, and\, 600$, with intervals of $5, 15\, and\, 100$ for training.

Table 2 displays the accuracy percentages of the collected data, demonstrating that our proposed alternative, which utilizes the MCNN technique, achieves higher accuracy compared to the current method [12].

Table 2: Accuracy rate

Accuracy rate	Hours	Epochs
80	5	20
95	15	200

97.1	100	60

4.4 Comparison

The comparison results reveal the current usage of support vector machine-based technique (SVM) and CNN methods. In this approach, the Monto Carlo algorithm and SVM with the Gabor filter are utilized to extract a set of templates [31-41]. Table 3 illustrates the comparative findings for face feature identification, highlighting the performance of the method in relation to other techniques. When compared to existing methodologies, our work delivers improved accuracy, particularly several types of feature extraction that aid in accurately obtaining the features.

Table 3: Accuracy comparison

Result	**Accuracy rates**	**Emotions**
SVM [30]	85-90	6
CNN [12]	79.98	**7**
MCNN (proposed)	**97.1**	7

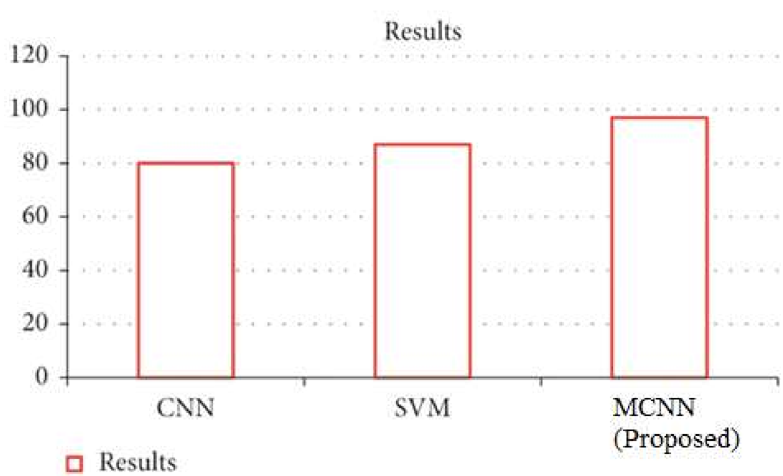

Fig 6: Comparison based on accuracy

For the existing & proposed methods, the accuracy results are shown in Fig. 6. Thus, when compared to the current procedure, our proposed approach produces better outcomes

5. Conclusion and Future Work

Our paper introduced a MCNN approach for emotional detection using deep learning algorithms. We utilized various facial characteristics along with suitable dimensional space reduction and applied kernel filters to sharpen the edges during the preprocessing procedure. The outcomes demonstrate that our MCNN approach achieved higher accuracy and improved the classification process compared to the current approach. The results are superior when compared to the present method with our suggested strategy. The model's capability looks to be sufficient to handle the task of accurate facial expression recognition at those resolutions. We can improve CNN performance by merging data from different stages: (b), cropping, and (f), adding noise, and using other data augmentation techniques. With the use of facial feature classification, our suggested MCNN identified 7 emotions with a high accuracy rate of 97.1%. Investigating image processing methods which may be seen as a deep learning augmentation data solution—is the focus of the highlighted study. It avoid data hunger and overfitting for little amounts of data. Future research will focus on expanding the study's set of features, determining the 10 various categories of facial emotions, and investigating automatic facial emotion recognition.

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