A STUDY ON THE DIFFERENT TECHNIQUES FOR FACIAL EMOTION IDENTIFICATION AND CLASSIFICATION

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Abstract - Facial expression plays a significant role in our everyday lives. These expressions help in identifying the frame of mind of people. Henceforth, it is used in various fields like medical psychology, criminal investigations, job recruitment, etc., to study human behaviour and analyze people. In the emerging field of artificial intelligence, various categories and analyses are developed to identify and classify facial emotions. Various methods have been implemented, from image analysis to live facial emotion recognition. In our proposed work, we have implemented micro-expression based real-time facial emotion recognition (FER) using a convolution neural network in conjunction with the artificial bee colony algorithm (ABC). Datasets like FER2013, Google Data Set, CK+ and in the wild dataset were used for the training process. We achieved a 95% to 99% accuracy in real-time video-based facial recognition.

Key Words: Facial Emotion Recognition (FER), Artificial Bee Colony (ABC), Multi-channel Convolution Neural Network (MCNN), Optical Flow Analysis, Empirical Wavelet Transform (EWT).

1. INTRODUCTION

Artificial Intelligence (AI) plays a critical role in facial emotion recognition (FER), using various algorithms and techniques to achieve a higher accuracy rate. These techniques are used daily in different fields to improve business strategies, psychology treatment, investigations, customer relationship management, education and personal assistant devices. Enormous datasets are available for the training process based on the state of emotion of individual faces, and the results are recorded and tabulated for future use.

Different criteria have been implemented, such as a combination of emotions, emotions based on scenario information, study-based emotions, real-time emotion detection, and emotions in social media. Various scholars have done detailed studies using varied techniques, algorithms, networks and datasets.

Non-verbal communication can be referred to as a part of facial emotion recognition, which helps identify individual emotions. These emotions can be identified in various channels such as images, videos and live feeds. State-of-the-art methods are used in the analysis of these emotions. The steps involved in the scenarios mentioned, the detection of the facial landmarks of an individual, detection of these expressions and classifying and categorizing these as emotions of the person based upon their facial expressions, are discussed.

2. ARTIFICIAL INTELLIGENCE IN EMOTION RECOGNITION

Artificial intelligence, machine learning and deep learning are playing a crucial role these days. They are the backbone of computer vision-based projects, providing a more excellent value of accuracy. Facial emotion identification uses advanced computer vision techniques; hence, it is used in a wide range of facial emotion-based applications.

2.1 APPLICATIONS

The Role of facial expression identification using artificial intelligence has been implemented in various fields. The body of the paper consists of numbered sections that present the main findings.

1. Facial Landmarks detection – Facial landmarks such as eyes, nose and mouth, which exhibit a person's emotion, can be detected and identified. These identified landmarks serve as the reference point for the emotional analysis of an individual.

2. Feature Extraction – This method forms the basis of facial landmark detection, where the shape and structure of the eyes, nose and mouth are studied. The curvature of the lips, the distance between the eyebrows, the positional changes of the eyelids, etc., are studied.

3. Machine learning techniques in AI models – Large datasets that have labelled facial emotions are trained using machine learning techniques to generate model files. These model files are used to recognize facial emotions based on the recognized patterns and correlation between the facial features and the emotions.

4. Classification of emotions - Various human emotions such as happiness, sadness, anger, surprise, disgust, and fear can be classified to identify a person's emotion in images, videos and in real-time.

5. Behavioral analysis in psychology – Depending on the individual's responses to various situations, in depth behavior can be studied using patterns, which help treat the patient.

6. In the field of medicine– An individual's emotional state can be monitored, and their mood swings can be detected. Hence, the mental health of a person can be observed.

7. Public Security – Security systems such as cameras can identify suspicious activities or harmful behavior of people in public, which can be used to enhance public safety.

8. Customer resource management – Product testing surveys use AI to analyze customers' facial expressions to gather information about their choices and preferences.

3. COMPARISON OF RELATED WORKS

3.1. Extreme Sparse Learning:
This technique is used to simultaneously learn the dictionary and classification model for the purpose of emotion recognition based on facial expressions. This method introduces an Optical Flow-based spatio-temporal descriptor and a classification model named Extreme Sparse Learning (ESL).

The proposed descriptor can recognize facial emotions robustly even when there are changes in the movement of the head. It can also capture both the intensity and dynamics of the facial emotions.

Moreover, the ESL classifier, achieved by adding the ELM (Extreme Learning Machine) error term to the conventional sparse representation's objective function, can learn a dictionary with discriminative and reconstructive properties.

The combined linear and non-linear objective functions are solved using an approach called the Class-Specific Matching Pursuit (CSMP). The paper [1] also presents a developed kernel extension of ESL, known as Kernel ESL (KESL).

The technique emphasizes that this is the first attempt to learn the sparse representation of the signal and a non-linear classifier based on sparse codes jointly in the literature [2]. The approach could efficiently handle facial expressions altered by movement, pose variations, illumination changes and partial occlusion. However, it may fail in extreme poses when certain parts of the face are not visible.

The system can efficiently handle noisy and imperfect data due to the sparse representation approach's ability to enhance noisy data using a dictionary learned from clean data. The paper suggests that the combined ESL and KESL algorithms exhibit good generalization performance on unseen test data.
The researchers evaluated their approach using several databases for facial emotion recognition tasks, including the Cohn-Kanade (CK+) Database.

3.2. Reduced Rank Reduction for Bimodal Emotion Recognition:
Bimodal Emotion Recognition strategically extracts important features from speech and facial expressions. This method employs the openSMILE feature extractor and the scale-invariant feature transform (SIFT). The authors propose the sparse kernel reduced-rank regression (SKRRR) fusion method to integrate the emotional features of these two modalities. They establish an optimal subspace that retains shared emotional information for both modalities, leading to the optimal features linked with the emotional information.

The paper [3] is divided into four parts: First, the kernel reduced-rank regression (KRRR) method is briefly detailed. Next, the sparse kernel reduced-rank regression (SKRRR) fusion approach and its associated algorithm are detailed. Third, the eNTERFACE' 05 and AFEW 4.0 bimodal emotion database, emotion feature extraction, monomodal emotion recognition and bimodal emotion recognition experiments are thoroughly explained.

The study also assesses the SKRRR method, the baseline, and a few advanced methodologies on the AFEW 4.0 database. It is found that the recognition results of various fusion methods, along with the SKRRR fusion method, outperform facial expression monomodal emotion recognition and speech monomodal emotion recognition.

The researchers described the eNTERFACE' 05 and AFEW 4.0 bimodal emotion database in the experiments section, along with details on emotion feature extraction and experimental results of monomodal and bimodal emotion recognition. The study contributes to the growing field of multimodal emotion recognition.

3.3. Spatial–Temporal Recurrent Neural Networks:
The article introduces a novel deep learning framework, the spatial–temporal recurrent neural network (STRNN), which incorporates both spatial and temporal information from signal sources for emotion recognition [4]. The STRNN uses a multidirectional recurrent neural network layer to capture emotion-related variations over time and a bi-directional RNN layer to discern temporal sequence dependencies. To enhance the discriminatory power of the model, the authors applied sparse projection to the hidden states in the spatial and temporal domains.

The study [5] examines emotion recognition tasks with EEG-based emotion detection and facial emotion recognition under a unified deep network framework, creating spatial-temporal volumes where EEG signals are organized spatially in electrode coordination.
This allows for the identification of critical emotion activation regions through sparse projection on underlying hidden states, weighing them adaptively. The research finds that emotion recognition is challenging due to disparities in human

experience and expression. Existing approaches like deep belief networks and canonical correlation analysis, which focus mainly on spatial correlations, can't fully address this problem. The STRNN, however, offers a promising method of understanding both spatial and temporal dependencies in emotion-related expressions.

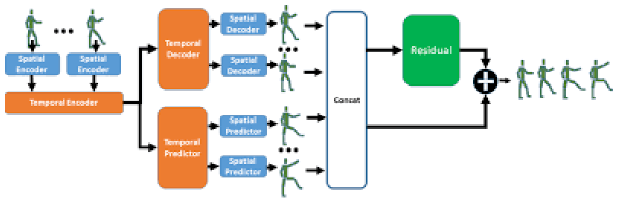

Fig -1: Spatial-Temporal Recurrent Neural Network

The experiments indicate that the STRNN outperforms existing state-of-the-art methods in the datasets used. Nonetheless, there is room for improvement and further research as the complexity of spatial dependencies and signal sources still poses some challenges.

Despite practical applications of devices like humanoid robots, emotion analysis remains problematic due to less tangibility. Therefore, researchers increasingly use electric devices to capture emotions expressed in signals like EEG signals, facial video sequences, and acoustic waves[6].

The authors emphasizes that human emotion analysis, critical to developing more human-like artificial intelligence systems, is gaining attention due to its potential applications in human-machine interaction. Thus, developing models like the STRNN has significant implications for future research and use in practical settings.

3.4. Real-time Algorithms:
Real-time Algorithms discuss the comparison of five different methods for real-time emotion recognition from facial images. The compared algorithms include AlexNet Convolutional Neural Networks (CNN) [7], Affdex CNN solution, a custom-made Facial Emotion Recognition - Convolutional Neural Network (FER-CNN) [8], Support Vector Machine (SVM) of Histogram of Oriented Gradients (HOG) features [9], and Artificial Neural Network of HOG features called Multilayer Perceptron (MLP).

The study uses the Affdex SDK, which allows for the detection of seven emotion metrics and other facial features to analyze complex facial expressions. Affdex is trained on a high volume of diverse, real-world data.

Results from testing these algorithms were based on experiments with eight volunteers. They were asked to express four emotions - happiness, sadness, anger and fear - which were recorded and processed through the algorithms. The resulting predictions from each algorithm were averaged to provide a single prediction for each emotion.

The paper also notes the use of SVM and MLP classifiers, with results shown in confusion matrices. Finally, it talks about the creation of the FER-CNN model involving convolutional layers and Softmax function for output and Viola-Jones algorithm for face extraction.

3.5. Multitask, Multilabel, and Multidomain Learning with Convolutional Networks:
This research [10] documents a study conducted by Gerard Pons and David Masip that focuses on creating a new approach to tackle discrete emotion recognition in various settings. The technique introduces the joint multitask approach and a novel dataset-wise selective sigmoid cross-entropy loss function, which helps carry out multiple tasks, handle multi-label, and solve multi-data set problems.

The proposal mainly addresses the dearth of large publicly labelled data sets. It demonstrates improvements in emotion recognition results when a joint training approach is applied utilizing a large dataset for AU (Action Unit) recognition. Their technique was assessed using the SFEW and Oulu-CASIA datasets for emotion recognition and the EmotioNet dataset for AU detection. The results were then compared to other models that undertake single tasks separately and to the classic multitask approach.

The approach displayed superior accuracy in emotion recognition across all the experiments and demonstrated the benefits of simultaneous learning of multiple correlated tasks [11]. It was shown that the model could successfully infer AU labels even for images that did not have them initially.
In a future study, the plan is to investigate the incorporation of landmark detection tasks in this multitask scheme and propose the inclusion of structural and geometrical cues to the appearance-based CNN to enhance the performance of emotion recognition.

The contributions to the field of computer vision, deep learning algorithms, and facial expression classification are also detailed. The research was notably supported partially by the Spanish Ministry of Science, Innovation and Universities and the NVIDIA Hardware Grant Program.

3.6. EEG-based Multimodal Deep Autoencoders:
The paper, titled "Expression-EEG Based Collaborative Multimodal Emotion Recognition Using Deep AutoEncoder" by H. Zhang [12], details research about human emotion recognition, which is an essential aspect of human-computer interaction. The study uses EEG signals, facial expressions, and various models to understand a person's emotional state.

The experiment involved showing 30 video clips to subjects and recording their EEG signals. Wavelet Packet Decomposition (WPD) was then applied to extract features from the preprocessed EEG data. A feature selection method based on a decision tree was used to select appropriate EEG features.

The research explains how the extracted EEG signals were processed via machine learning methods, including Support Vector Machine (SVM), K-Nearest Neighbor, linear discriminant analysis, logistic regression, and decision tree. In some cases, Principal Component Analysis (PCA) was used for dimension reduction.

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The results showed that the use of a multi-modal fusion model for emotion recognition was more successful than using each individual mode. Zhang also stated that emotion recognition accuracy was higher when EEG features were obtained via more advanced extraction algorithms than traditional methods.

3.7. GA and Adaboost for Hybrid Deep Features

Research by N. Samadiani et al. [13] discusses a method for recognizing happy emotions from unconstrained videos using 3D Hybrid Deep Features. The document begins by recognizing the importance of emotion recognition research and its application in numerous fields, such as advertising, lie detection, disease diagnosis, and tailored recommendations in interconnected systems.

The authors selected three benchmark facial expression datasets (AM-FED +, AFEW, and MELD) to evaluate their approach, which involves a fusion of both feature levels and decision levels. The study [14] proposes a novel HappyER-DDF method that uses a 3D-Inception-ResNet neural network to extract spatial-temporal features from video frames. As a part of their methodology, a Long-Short Term Memory (LSTM) unit is included to extract the dynamics of facial expressions over time.

Superior recognition performance was demonstrated through experimental evaluation. Happy emotion detection accuracy on the AM-FED +, AFEW, and MELD datasets was 95.97%, 94.89%, and 91.14%, respectively. The results prove that combining textural and landmark features leads to higher accuracy, particularly with feature-level fusion.

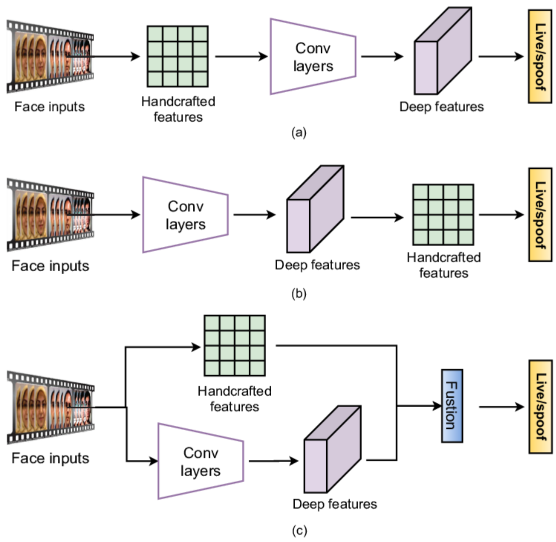

Fig -2: Hybrid Deep Features

This research on single emotion recognition could also effectively handle challenging conditions like head pose variations, illumination changes, and race diversity [9]. The proposed approach recognises spontaneous emotions from complex real-world settings, providing an opportunity for high-accuracy emotion detection in practical applications.

3.8. Facial Emotion Recognition Using Ensemble based Multi-Dimensional DeepNets:

This research discusses the architecture of a proposed deep learning system using the Inception V3 model. The model is chosen because it consumes less memory (around 92MB), reaches a topological depth of 159 layers, and contains 23 million parameters. It is trained using a 3x3 standard convolutional kernel, with a Rectified Linear Unit (ReLU) and a pooling layer included to flatten the model for supply to the fully connected classification layer.

The system also includes modified architecture sub-modules (A, C and E) to factorize parameter values and sub-modules (B and D) to reduce grid size. As a result, the proposed DeepNet model [15] takes less time to train and emphasizes certain special features in the inputs. Moreover, the Inception V3 model [16] utilizes a 1x1 2D convolution filter for faster training by shrinking the number of channels, thus cutting computational costs and enhancing the system's performance.

The neural network processes the Spatio-temporal feature vectors encoded to yield classes, which are categorized into mapping supplied for network training. The remaining comparable models were tested and found to have a maximum accuracy based on earlier methodology that fell between 38% and 64%. After 20 training epochs, the researchers' suggested model produced an overall training accuracy of more than 94% and an average validation accuracy of about 85% for the various classes of micro emotions being detected. Compared to the other models under study, this is a vast improvement.

3.9. Swarm Intelligence based Modified Convolutional Neural Networks:

In this proposed study, the authors [17] introduce a novel methodology for recognizing and classifying micro-expressions in facial videos. This methodology involves a Multi-Channel Convolutional Neural Network (MCNN) based on the Artificial Bee Colony (ABC) algorithm.

The MCNN-ABC procedure initially utilizes Histogram Equalization (HE) to enhance the contrast of images. The Empirical Wavelet Transform (EWT) is then employed to extract the features from the facial images.

Finally, MCNN is used to recognize and classify emotional facial expressions. The last step involves tuning the hyperparameters using the ABC algorithm [17]. The authors state that this has the additional advantage of making the network converge in a shorter amount of time with optimal results instead of manually tweaking the parameters to obtain the desired outcome.

The experiment was carried out using a computer with an Intel i7 core CPU, 32 GB of RAM, and an Nvidia GTX 1080 GPU with 2560 CUDA Cores and 320 GB/s of memory bandwidth. The experiment was also converted to operate on the Google Cloud platform's TPU architecture. To train the network in 7 micro expressional classes, 28,709 picture data were used. Up to 95% - 99% accuracy was attained in the lab test scenario.

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Table -1: Algorithms and Efficiency

Paper Title	Algorithm	Advantages / Disadvantages	Accuracy
Robust Representation and Recognition of Facial Emotions Using Extreme Sparse Learning (2015)	Extreme Sparse Learning (ESL)	Robustness in illumination changes, occlusion, and pose variations / Failed to detect emotions during facial muscle movement during speaking	60%
Sparse Kernel Reduced-rank Regression for Bimodal Emotion Recognition from Facial Expression and Speech (2016)	SVM classifier & SR classifier	Monomodal & Bimodal emotion recognition/ Needs improvement in emotion classification	87:02% (linear kernel) & 87:46% (Gaussian kernel)
Spatial-Temporal Recurrent Neural Network for Emotion Recognition (2018)	Multidirectional RNN & STRNN	EEG is used for Salient Emotion Detection/Relatively high confusions appear between three pairs of expressions: 1) contempt versus angry; 2) contempt versus fear; and 3) contempt versus sadness, which may be intuitively due to the similar muscle deformations	TRNN 86.06% & STRNN 89.50%
Real-time Algorithms for Facial Emotion Recognition: A Comparison of Different Approaches (2018)	Viola-Jones algorithm	Real-time study of facial emotion recognition/ limited emotions is recognized	84.85%
Multitask, Multilabel, and Multidomain Learning With Convolutional Networks for Emotion Recognition (2020)	Multi-domain Convolutional Neural Network	Discrete emotion recognition is recognized/ geometrical cues to the appearance-based CNN might boost the performance of the emotion recognition task can be added	84.02%
Expression-EEG Based Collaborative Multimodal Emotion Recognition Using Deep AutoEncoder (2020)	CNN	Expression signals and EEG signals are used as emotion signals using a multi-modal emotion recognition	85.71%.
Happy Emotion Recognition From Unconstrained Videos Using 3D Hybrid Deep Features (2021)	Genetic algorithm & AdaBoost algorithm	ResNet frameworks, 3D version of Inception-ResNet architecture has been implemented/ unconstrained datasets can be used in future.	HappyER-DDF - 95.97%, AM-FEDC dataset - 94.89% & AFEW dataset - 91.14%
Facial Emotion Recognition Using Swarm Optimized Multi-Dimensional DeepNets with Losses Calculated by Cross-Entropy Function (2023)	Ensemble learning algorithm with Artificial Bee Colony	The learning and convergence rates of the proposed architecture are pretty high, and the output in recognition rates is more accurate than the existing methods.	Training accuracy: 94%
Facial Micro Emotion Detection and Classification Using Swarm Intelligence based Modified Convolutional Network (2023)	CNN combined with swarm optimization	Real-time facial emotion recognition has been implemented using a modified Convolutional Neural Network with an Artificial Bee Colony (ABC) algorithm	99.45%

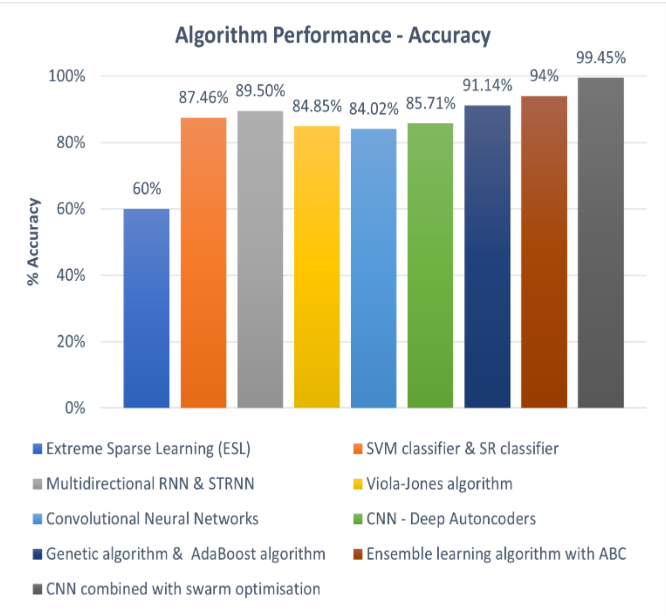

Fig -3: Accuracy of different algorithms

4. CONCLUSIONS

The primary goal of this research is to enhance the performance of Neural Networks in the realm of micro-expression analysis, specifically in recognition and classification tasks. This area presents challenges due to the extremely brief duration of captured apex frames and the limited dataset available for training the network.
The proposed model tackles these challenges by introducing a preprocessing phase that involves utilizing additional learners through boosting and a swarm-based flow vector detection mechanism. These components work together to simplify the operation of the modified Convolutional Neural Network (CNN) kernel. As a result, the model addresses issues like poor lighting conditions, variations in facial orientation and topological structures, as well as color and contrast discrepancies.

Notably, the model is engineered to have low memory requirements and a reduced training time, optimizing the CNN performance. The architecture exhibits high learning and convergence rates, leading to more accurate recognition outcomes compared to existing methods. Notably, the Deep Learning ConvNet's hyperparameters can be fine-tuned for optimal performance, enabling real-time analysis of micro-expressions in live video feeds. This application holds immense potential in various domains, including emotional intelligence assessment, deep fake detection, medical research, market surveys, and job recruitment.

The technology's market potential is projected to reach $56 billion by 2024. To extend this research, one avenue is to incorporate audio components into the training process, enabling the creation of a more precise model that captures the interplay between spoken context and corresponding displayed micro-expressions.

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