JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Review of Facial Expression Recognition using Machine Learning

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Abstract: How a person seems to be feeling In interpersonal communication, one of the most difficult and vital skills to master is the ability to give and receive an acknowledgement. It is easy to tell how people feel and what they aim to accomplish by they're facial expressions. Nonverbal communication relies heavily on facial expressions. Automated facial expression identification is becoming more dependent on deep neural networks. In part, this is because FER has gone from lab-controlled to real-world situations, where deep learning methods have proven useful in a variety of industries. Two major issues have been addressed in recent deep FER systems: overfitting, which occurs when there isn't enough training data, and elements that don't have anything to do with the expression of the subject, such as illumination, and head position, and identification bias. This study provides an in-depth examination of deep FER, which includes datasets and approaches that shed light on the issues at hand. To begin, we'll go through the datasets that the general public has access to. These datasets have been extensively studied in the scientific literature, and a variety of data selection and assessment techniques have been used. This is followed by an explanation of the standard deep FER system pipeline, as well as background information and recommendations for successful implementations at each level. For deep FER, we look at the most cutting-edge deep neural networks and training approaches for FER based on static photographs and dynamic image sequences, as well as advantages and drawbacks. Other commonly used benchmarks are included in this section as well. Then, in order to make our poll even more helpful, we add more topics and purposes to it. Last but not least, we examine the challenges and opportunities that remain in this sector and how to construct robust deep FER systems in the near future.

Keywords: FER, CNN, Machine Learning, Facial Expression, geometry-based Feature Extraction.

I. INTRODUCTION

Expressions on people's faces are highly significant components of the communication process between individuals. Words and deeds go hand in hand the vast majority of the time in communication [1]. Expressions on one's face may convey meaning even in the absence of spoken language. [2] A person's facial expressions are the subtle cues that convey the larger meaning. Both humans and animals can communicate with one another even without the use of words. They can do this via maintaining eye contact, gestures, facial emotions, body language, and paralanguage.

Eye contact is an essential component of communication because it facilitates the exchange of information between individuals [3]. Maintaining eye contact with other people helps you connect with them and regulates what they say and how they say it. There is the happy grin, the sad ones, the angry one, the disgusted one, the surprised one, and the scared one [4]. When someone smiles, it reveals that they are content and causes the corners of their eyes to tilt upwards. The expression of sadness, which may be recognised by its telltale arched, crooked eyebrows and frown, is known as the sense of being loose [5]. Things that are undesirable or inconvenient tend to set individuals off in an angry mood. When someone is upset, their eyelids become thin and strained, and their eyebrows are drawn together. [6]

The phase of ER in which characteristics are extracted and put together is the most crucial aspect of the process. There are two types of feature extraction: those based on geometry and those based on appearance [7]. Geometry-based feature extraction is the more common kind. Classification is one of the most significant aspects of categorising facial emotions like a grin, sorrow, anger, contempt, surprise, and fear into groups. Examples of these expressions include: The eye, mouth, nose, eyebrows, and other facial elements are included in the geometrically based feature extraction, while the specific region of the face is included in the appearance-based feature extraction [8].

The face will give out three distinct types of signals the majority of the time, static, slow, and quick [9]. The static signs include skin colour, which includes things like pigmentation and greasy deposits, facial shape, bone structure, cartilage, and the form, placement, and size of items like the eyes, nose, and mouth [10]. The slow signals include wrinkles that never go away and changes in the face's appearance due to the passage of time, such as differences in muscle tone and skin texture [11].

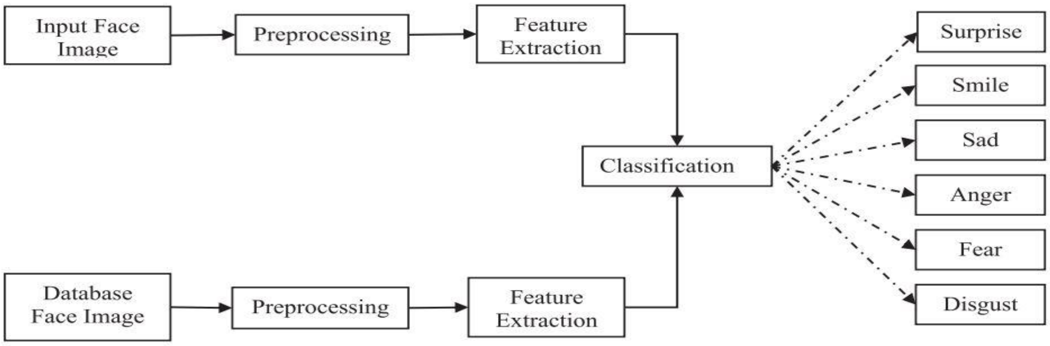

Figure 1. The architecture of facial expression recognition system.

In recent years, deep learning and, more specifically, convolutional neural networks (CNNs) have made it possible to pull out and learn a lot of information that can be used in facial expression recognition systems. Because of this, the quality of these systems has gotten a lot better. But it's important to remember that most of the clues come from just a few places, like the lips and the eyes, when it comes to facial expressions. Other parts of the face, like the ears and the hair, don't have much to do with the output. This means that the machine learning framework should, ideally, focus only on the important parts of the face and pay less attention to the other parts [12].

Human-machine contact has a lot of potential that can only be used to its fullest with clear and concise communication. Communication can happen both verbally and nonverbally. A critical example of the latter is figuring out how someone is feeling. Different ways, such as a person's speech, facial expression, body language, etc., can be used to figure out what they are thinking and feeling. [13] Some psychologists think that about 55 per cent of all communication is done through facial expressions. Even without words, a person's facial expressions can tell a lot about their feelings. Face expressions show how a person is feeling and what they are thinking. This is because facial muscles can move into different positions. Paying close attention to someone's facial expressions can help you figure out how they feel, what they plan to do, and other things like that. Emotion recognition through facial analysis is becoming more popular because it can be used in many places, like robotics, where the connection between people and machines is very important. Analysis of a person's facial expressions to figure out what they're feeling is also used for biometric security checks and surveillance, among other things. [14]

At this early stage in developing partnerships between humans and machines, communication is a key part of making these interactions better. It shouldn't surprise that people prefer to use natural ways of communicating with technology, like the languages they have built up over time. Emotions, which create a logical way of passing on information, are another way that people naturally communicate with each other without using words. It would be helpful if robots could understand how people feel, making communication a step further. Emotion recognition can be done in a number of ways, but the most important ones are based on speech and facial expressions. Deep learning and more traditional types of machine learning are two examples of how facial expressions and sounds can be used to figure out how someone is feeling. This article aims to use machine learning methods that don't use deep learning, which is often called "traditional machine learning methods," to cut down on the amount of computing and complexity that is needed. Methods like COD, HOG, and KNN Classifiers that are easier to understand are used to figure out how someone feels based on their appearance. [15].

II. BASIC TERMINOLOGIES

Face Detection: Determining whether or not a photograph contains a face is known as face detection. To do this, we need to have a broad understanding of what a face looks like. It's encouraging to see that people's faces aren't all that dissimilar. The overall framework of a face is comprised of a person's mouth, nose, eyes, forehead, and chin. All of us share these facial features. It is a method for classifying individuals into two distinct categories: those who have faces and those who do not. For instance, using a process known as object class detection, one may identify faces. The process of determining the position of each item in an image, as well as its size and whether or not it belongs to a certain class, is referred to as object-class detection. It is possible to infer that from this [16]:

Figure 1. Detection of a face [16]

Facial Recognition: This element of the system uses a database of people's faces to identify probable matches [17] for the person being sought.
Using facial recognition software, the computer determines whether the person being verified is, in fact, whom they claim to be.
Expressions of the Face A facial expression may be described as a movement or position of the muscles under the skin of the face. Other individuals may tell a lot about someone's emotional state just by observing their body language. It's a means to communicate without the need for language. People's ability to get along with one another is influenced by their ability to communicate effectively. In terms of frequency, the most common ones are:

Figure 2. Expressions of the face [17]

III. LITERATURE REVIEW

The final step is to utilise a facial landmark detection library in order to recognise facial landmarks that are specific to each individual human face. After that, the human face is cut in half vertically, creating an upper and lower section. This allows the required traits to be extracted from any region of the face. Both geometric and texture-based components are taken into consideration in the model that has been presented. The next step, which follows the feature extraction process, is the generation of a vector of normalised features. These feature vectors are put through the training process of a three-layer MLP, which results in an accuracy of 96 percent on the test set [18].

The suggested model has a face identification accuracy of 92.46 percent with p less than 0.05, which is higher than the accuracy of 86 percent that the CNN Classifiers have. It was found that the recommended model was more accurate than the Machine learning technique [19] after applying the Unsupervised Machine Learning algorithm to the provided model and comparing it to the CNN Classifiers method. This was done in order to evaluate which method was superior.

Our objective is to highlight the differences and similarities of the aforementioned methodologies and the emerging hybrid and ensemble learning trend in FER systems. We want to provide a general framework for each type of learning and investigate the various technologies that can be used as its constituents. At the same time, we want to make this framework as flexible as possible. Between the years 2014 and 2020, we want to do a more in-depth and comprehensive study on commonly used datasets, both in terms of our competitive performances and our experimental comparisons. The next step that we will take is to broaden the scope of our survey such that it includes the application scenarios that we are already using in Vietnam [20].

In order to reduce the total number of parameters and produce a greater number of feature maps, the ghost-module design makes use of a number of different basic linear transformations. The GCNN is able to effectively extract and categorise face expression features because to its design, which is based on the Ghost module. When applied to three different FER databases (the RAF-DB database, the FER2013 database, and the FERPlus database), the results of experiments have indicated that this strategy beats all other advanced techniques [21].

This is the first work that we are aware of that investigates the usage of GAN to analyse manifold-valued representations in order to tackle the problem of dynamic facial expression generation. We perform a quantitative and qualitative investigation of our recommended strategy using two publicly accessible datasets, Oulu-CASIA and MUG Facial Expression. According to the results of our experiments, our technology is able to effectively make realistic films that have nonstop action, a realistic appearance, and the preservation of their identities. In addition, we show that our technique is capable of successfully creating dynamic facial expressions, transferring dynamic facial expressions, and enriching training data for improved emotion recognition models [22].

During the course of this study project, we investigated a wide range of methodologies, all the way up to and including accurate observations, for measuring the efficacy of emotions. This paper analyses previous research on facial expression recognition that was published between the years 2007 and 2021. According to the findings of these studies, using an electroencephalogram (EEG) signal can achieve an accuracy of 95.20 per cent, and combining statistical features and a neural network with EEG data can achieve an accuracy of 95 per cent. Both of these levels of accuracy can be achieved by using an EEG. The typical accuracy varies from 63 to 73 per cent [23], and it is achieved by using both the EEG data and facial expressions.

Users are given access to a user-friendly method that can automatically build triplets for a system. This enables users to annotate correspondences in a way that is both easy and time-effective. We developed a neural network that is capable of translating human expressions into those of avatars by taking advantage of geometric and perceptual correspondences. Extensive experimental findings and user assessments show that even nonprofessional users may be able to get high-quality facial expression retargeting outcomes with less time and effort when utilising our approach [24]. [citation needed] This is shown by the fact that the outcomes were achieved using our method with much less time and labour.

A convolutional neural network is used throughout the process of teaching the model to identify a variety of facial expressions. The Raspberry Pi 3B+ board and the Pi-Camera are both used in the real-time testing that is carried out. PyQt5, which is an acronym that stands for "graphical user toolkit," is the tool that is used to construct the graphical user interface for the system (GUI). The results of the test indicate that the method being proposed has a high level of identification accuracy, reaching up to 99.88 per cent [25].

Because there is not a single model or framework that is capable of separating the many distinct kinds of sensations, it is possible that at times it may be difficult to recognise them. Recognising the range of emotions communicated via facial expressions may also provide a number of issues. The expressions that appear on a person's face are a kind of nonverbal communication that is thought to represent the individual's inner feelings. In this kind of contact, the expressions on one's face are of great significance. Throughout the process of emotion detection, machine learning strategies, as well as Deep Learning and Neural Network algorithms, are used. This article shows how Convolutional Neural Networks may be used to identify feelings and emotions (CNNs). The suggested approach is able to recognise a variety of emotions, including rage, contempt, happiness, fear, sorrow, tranquilly, and surprise [26].

In addition, we recommend making use of an exogenous dispelling loss in order to get rid of any extraneous information that could be present in the endogenous representation. As a result, the exogenous data is used in a throwable method not once but twice. In the beginning, it is employed as a conditioning variable for the objective task, and then, later on, it is used as an invariance generator for the endogenous representation. Both of these applications are susceptible to being rejected. The name for this kind of operation is "throwable information networks" (THIN). We provide experimental validation of THIN in a variety of contexts where it is possible to uncover exogenous information. Among these options is the recognition of digits while being subjected to severe rotations and displaying a wide range of sizes and forms. We also apply it to FER, but this time we use identity as the exogenous variable in the model. We demonstrate [27] that THIN is superior to the most cutting-edge methods that are presently in use by analysing a variety of difficult datasets.

The combination of EDA and facial expression data achieved an accuracy of 90.91 per cent, a sensitivity of one hundred per cent, and a specificity of 81.82 per cent when it came to classifying clinically significant pain versus clinically nonsignificant pain. Both EDA and facial expression data provide sensitivities and specificities that are significantly higher than chance, but the combination of the two significantly improved the classification of clinically significant pain versus clinically nonsignificant pain. The complex pain response may be addressed using many treatment modalities simultaneously. This study provides evidence for the utility of a weighted maximum likelihood algorithm as a novel feature selection method for electronic data acquisition (EDA) and video facial expression data, as well as a precise and objective automated classification algorithm that is able to differentiate between clinically significant pain and clinically nonsignificant pain in children [28].

IV. FACIAL EXPRESSION RECOGNITION

A person's face consists of bones, muscles, and skin the vast majority of the time When these muscles contract and relax, the form of the face changes. The quickest method to convey information is via one's facial expressions. It's possible that a face expression detection system may allow people and machines to communicate in a more natural way. According to Ekman and Friesen, facial features such as the brows, lips, eyes and cheeks contract as a rapid indicator of a person's emotional state. How well someone can be identified is affected by this. In addition, there are six universally recognised expressions: joyful, sad, afraid, disgusted, furious, and startled. These six are universally recognised expressions. Three phases are required for facial emotion recognition: face detection, feature extraction, and classification.

Figure 3. Face and Emotion Detection

Face recognition is the first step in identifying various facial expressions and emotions. In order to extract facial features, an image must first be normalised before feature points can be detected, lines aligned, the face region located, and a rectangle cropped. For this, the face model serves as a helpful reference point. Multiple faces may be detected using the face detection approach.

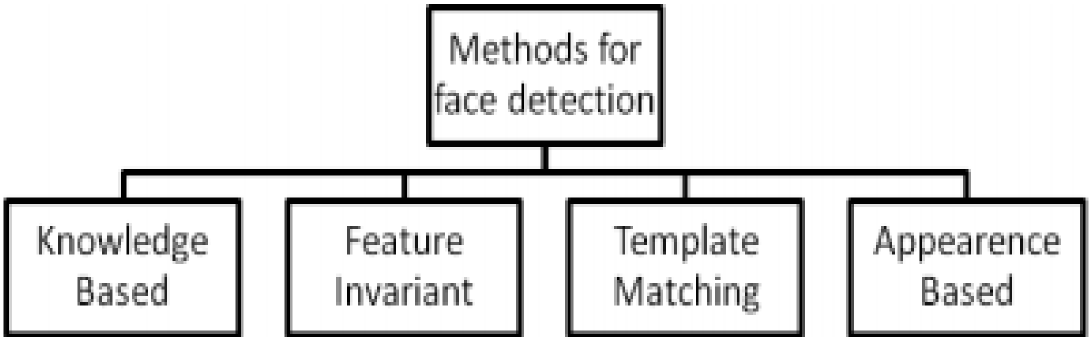

Figure 4. Techniques for the identification of faces

V. FEATURE MINING

The process of feature extraction takes pixel data and turns it into a more detailed representation of the face's form, motion, colour, and texture. This may be done in order to increase face recognition capabilities. Feature extraction is often used to minimise the dimensionality of the input space. Given that pattern recognition relies on the reduction approach, it should be able to save a significant quantity of data. It is possible to extract attributes using a variety of methods.

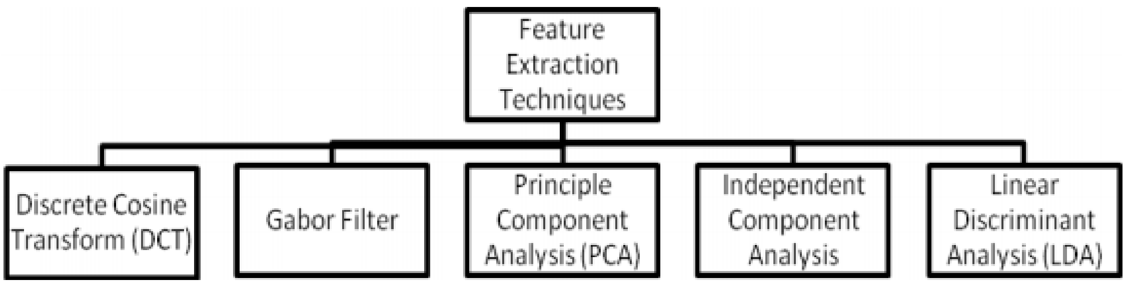

Figure 5. Retrieval of a feature

VI. PREVIOUS RESEARCH PAPERS ON FACIAL EXPRESSION RECOGNITION WERE REVIEWED

Table 1. Research Papers on the Recognition of Facial Expressions

EXPRESSION S	FACE DETECTION	FEATURE EXTRACTION	EXPRESSION CLASSIFICATION	ACCURACY (%)
Angry, disgust, fear, happy, neutral, sad	Appearance based	Bezier-curve, k-mean	Feed-forward neural network	85
Angry, disgust, fear, happy, neutral, sadness, surprise	JAFFE database (fusion approach: GRAY+SRC and ALBP+SRC)	Gabor filter	SRC	70
Happy, sad, normal	Appearance based	DCT	NN	-
Joy, sadness, surprise, angry, disgust, fear	(1) Cohn-kanade database (2) BHU facial expression database	FPDRC+CARC +SDEP	RBF	(1)88.7 (2)87.8
Angry, disgust, fear, happy, neutral, sadness, surprise	JAFFE database (Fusion approach: GARY+SRC and CLBP+SRC)	Gabor filter	SRC	69.52
Angry, disgust, fear, happy, neutral, sadness, surprise	JAFFE database	t-SNE	(1) SVM (2) Ada boost M2	(1) 90.3 (2) 94.5
Anger, joy, sad, surprise, fear, disgust	Cohn-kanade database	FICA	HMM	92.85
Angry, disgust, fear, happy, neutral, sadness, surprise	JAFFE database (1)Gray (2)LBP (3)Gabor	Gabor filter	SRC (D-KSVD)	(1)85.7 (2)78.6 (3)94.3
Angry, disgust, fear, happy, neutral, sadness, surprise	JAFFE database	NMF	SVM	66.2
Angry, fear, disgust, surprise, sad	Feature invarian	AAM	(1)Euclidean distance method (2)ANFIS	(1)90-95 (2)close to 100

VII. CONCLUSION

Two major potential developments that have been suggested in recent works are FER for side view faces that use subjective information of facial sub-regions and the use of multiple factors to identify the location of the face for real-time applications. Both of these advances are critical to the growth of face recognition technology. FER is utilised in forensics, medicine, and robotics, among other real-time applications. It is possible to build algorithms after reading the survey paper, the details of which will depend on their accuracy and degree of complexity. Furthermore, depending on the demands of the hardware implementation, low-cost implementations of hardware implementations may be advantageous. This paper has studied several techniques for preprocessing, feature extraction, classification, and significant contribution analysis. The database is used for the performance analysis, with the complexity rate, recognition accuracy, and major contributions acting as the foundation. In this part, we look at things like preprocessing capabilities and feature extraction and the expression count. To achieve the research's goal, a thorough examination of the capabilities and benefits of algorithms will be conducted. The ROI segmentation approach utilised in preprocessing produces the best results (94,3 per cent) when it comes to precision. Feature extraction demonstrates that the accuracy of GFs is always between 82.5 and 94.3 per cent. The SVM classifier has a maximum identification accuracy of 94.3 per cent and can recognise various emotions, including disgust, sorrow, surprise, rage, fear, and neutral. Its maximal recognition accuracy is determined by how well it recognises certain facial expressions. The JAFFE and CK databases play an important part in a more effective method of achieving high performance in 2D FER than others.

Reference

[1] X. Zhang, F. Zhang and C. Xu, "Joint Expression Synthesis and Representation Learning for Facial Expression Recognition," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 3, pp. 1681-1695, March 2022, doi: 10.1109/TCSVT.2021.3056098.

[2] Z. Hu and C. Yan, "Lightweight Multi-Scale Network with Attention for Facial Expression Recognition," 2021 4th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), 2021, pp. 695-698, doi: 10.1109/AEMCSE51986.2021.00143.

[3] Q. Xu and N. Zhao, "A Facial Expression Recognition Algorithm based on CNN and LBP Feature," 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 2020, pp. 2304-2308, doi: 10.1109/ITNEC48623.2020.9084763.

[4] S. Roy Supta, M. Rifath Sahriar, M. G. Rashed, D. Das and R. Yasmin, "An Effective Facial Expression Recognition System," 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), 2020, pp. 66-69, doi: 10.1109/WIECON-ECE52138.2020.9397965.

[5] X. Xu, Z. Ruan and L. Yang, "Facial Expression Recognition Based on Graph Neural Network," 2020 IEEE 5th International Conference on Image, Vision and Computing (ICIVC), 2020, pp. 211-214, doi: 10.1109/ICIVC50857.2020.9177430.

[6] M. M. Kabir, T. A. Anik, M. S. Abid, M. F. Mridha and M. A. Hamid, "Facial Expression Recognition Using CNN-LSTM Approach," 2021 International Conference on Science & Contemporary Technologies (ICSCT), 2021, pp. 1-6, doi: 10.1109/ICSCT53883.2021.9642571.

[7] A. Kreinis, T. Damri, T. Leon, M. Litvak and I. Rabaev, "Telemoji: A video chat with automated recognition of facial expressions," 2021 International Conference on Visual Communications and Image Processing (VCIP), 2021, pp. 1-1, doi: 10.1109/VCIP53242.2021.9675330.

[8] L. Zhang, C. Xu and S. Li, "Facial Expression Recognition of Infants Based on Multi-Stream CNN Fusion Network," 2020 IEEE 5th International Conference on Signal and Image Processing (ICSIP), 2020, pp. 37-41, doi: 10.1109/ICSIP49896.2020.9339265.

[9] H. Liu, J. Zeng and S. Shan, "Facial Expression Recognition for In-the-wild Videos," 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), 2020, pp. 615-618, doi: 10.1109/FG47880.2020.00102.

[10] J. L. Joseph and S. P. Mathew, "Facial Expression Recognition for the Blind Using Deep Learning," 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON), 2021, pp. 1-5, doi: 10.1109/GUCON50781.2021.9574035.

[11] Y. Xia, W. Zheng, Y. Wang, H. Yu, J. Dong and F. -Y. Wang, "Local and Global Perception Generative Adversarial Network for Facial Expression Synthesis," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 3, pp. 1443-1452, March 2022, doi: 10.1109/TCSVT.2021.3074032.

[12] H. Zhang, W. Su, J. Yu and Z. Wang, "Identity–Expression Dual Branch Network for Facial Expression Recognition," in IEEE Transactions on Cognitive and Developmental Systems, vol. 13, no. 4, pp. 898-911, Dec. 2021, doi: 10.1109/TCDS.2020.3034807.

[13] D. Poux, B. Allaert, N. Ihaddadene, I. M. Bilasco, C. Djeraba and M. Bennamoun, "Dynamic Facial Expression Recognition Under Partial Occlusion With Optical Flow Reconstruction," in IEEE Transactions on Image Processing, vol. 31, pp. 446-457, 2022, doi: 10.1109/TIP.2021.3129120.

[14] C. Jia, C. L. Li and Z. Ying, "Facial expression recognition based on the ensemble learning of CNNs," 2020 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), 2020, pp. 1-5, doi: 10.1109/ICSPCC50002.2020.9259543.

[15] J. Zhang, X. Yao, Y. Zhang, N. Xu and X. Liu, "Spectral Norm Normalized Network for Facial Expression Generation," 2020 IEEE International Conference on Progress in Informatics and Computing (PIC), 2020, pp. 202-206, doi: 10.1109/PIC50277.2020.9350747.

[16] F. Zhang, T. Zhang, Q. Mao and C. Xu, "Geometry Guided Pose-Invariant Facial Expression Recognition," in IEEE Transactions on Image Processing, vol. 29, pp. 4445-4460, 2020, doi: 10.1109/TIP.2020.2972114.

[17] B. Zhang, D. Wei, Q. Zhang, W. Si, X. Li and Q. Zhu, "Classroom monitoring system based on facial expression recognition," 2021 20th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), 2021, pp. 108-111, doi: 10.1109/DCABES52998.2021.00034.

[18] M. A. Haghpanah, E. Saeedizade, M. T. Masouleh and A. Kalhor, "Real-Time Facial Expression Recognition using Facial Landmarks and Neural Networks," 2022 International Conference on Machine Vision and Image Processing (MVIP), 2022, pp. 1-7, doi: 10.1109/MVIP53647.2022.9738754.

[19] V. B and D. S. J. J. Thangaraj, "Innovative Facial Expression Identification for Criminal Identification using Unsupervised Machine Learning and Compare the Accuracy with CNN Classifiers," 2022 International Conference on Business Analytics for Technology and Security (ICBATS), 2022, pp. 1-4, doi: 10.1109/ICBATS54253.2022.9759043.

[20] V. -T. Dang, H. -Q. Do, V. -V. Vu and B. Yoon, "Facial Expression Recognition: A Survey and its Applications," 2022 24th International Conference on Advanced Communication Technology (ICACT), 2022, pp. 359-367, doi: 10.23919/ICACT53585.2022.9728930.

[21] B. Fang, G. Chen and J. He, "Ghost-based Convolutional Neural Network for Effective Facial Expression Recognition," 2022 International Conference on Machine Learning and Knowledge Engineering (MLKE), 2022, pp. 121-124, doi: 10.1109/MLKE55170.2022.00029.

[22] N. Otberdout, M. Daoudi, A. Kacem, L. Ballihi and S. Berretti, "Dynamic Facial Expression Generation on Hilbert Hypersphere With Conditional Wasserstein Generative Adversarial Nets," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 2, pp. 848-863, 1 Feb. 2022, doi: 10.1109/TPAMI.2020.3002500.

[23] N. Kumar and N. Gupta, "A Comprehensive Study on Machine Learning Approaches for Emotion Recognition," 2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP), 2022, pp. 1-5, doi: 10.1109/AISP53593.2022.9760652.

[24] J. Zhang, K. Chen and J. Zheng, "Facial Expression Retargeting From Human to Avatar Made Easy," in IEEE Transactions on Visualization and Computer Graphics, vol. 28, no. 2, pp. 1274-1287, 1 Feb. 2022, doi: 10.1109/TVCG.2020.3013876.

[25] P. Dhope and M. B. Neelagar, "Real-Time Emotion Recognition from Facial Expressions using Artificial Intelligence," 2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP), 2022, pp. 1-6, doi: 10.1109/AISP53593.2022.9760654.

[26] S. K. Singh, R. K. Thakur, S. Kumar and R. Anand, "Deep Learning and Machine Learning based Facial Emotion Detection using CNN," 2022 9th International Conference on Computing for Sustainable Global Development (INDIACom), 2022, pp. 530-535, doi: 10.23919/INDIACom54597.2022.9763165.

[27] E. Arnaud, A. Dapogny and K. Bailly, "THIN: THrowable Information Networks and Application for Facial Expression Recognition In The Wild," in IEEE Transactions on Affective Computing, doi: 10.1109/TAFFC.2022.3144439.

[28] B. T. Susam et al., "Automated Pain Assessment in Children Using Electrodermal Activity and Video Data Fusion via Machine Learning," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 1, pp. 422-431, Jan. 2022, doi: 10.1109/TBME.2021.3096137.