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Advancements in Facial Expression-Based Automatic Emotion Identification Using Deep Learning

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Abstract: Facial expression-based automatic emotion identification is an intriguing research subject that has found applications in areas as diverse as security, healthcare, and the human-computer interface. Researchers in this area seek to improve computer prediction by creating methods for reading and encoding facial emotions. As deep learning has shown to be so effective, many designs have been used to maximize its potential. This paper's goal is to examine recent efforts towards fully autonomous FER with the use of deep learning. The researcher emphasizes these processing contributions, architectures and databases, and then illustrate the progress accomplished by comparing the offered approaches and acquired outcomes. This paper’s goal is to aid and direct scholars by surveying current efforts and offering suggestions for how to further the area.

Keywords: Facial Expression; Human Computer Interaction; Facial Emotions; Deep Learning.

1. Introduction

Automatic facial expression analysis is an intriguing and challenging issue with applications in fields as diverse as human-computer interaction and data-driven animation. Accurate face representations generated from raw facial pictures are crucial for facial expression recognition. This vast and important area of research brings together two seemingly unrelated areas: artificial intelligence and the capacity to discern human emotions in cognition (AI). Emotional states of humans may be deduced from a variety of sensor-collected inputs, including speech, tone of voice, and physiological responses. In 1967, Mehrabian demonstrated that the visual medium accounts for 55% of emotional information, whereas the aural medium accounts for 38% and words account for just 7%. Most academics are interested in this strategy since facial expressions are the first signal to transmit emotional state during conversation. As we've seen, security is the primary motivation for establishing one's identity. Identifiers may be based on a user's fingerprints, voiceprints, passwords, retinal scans, etc. Knowing the other person's motivation might help you avoid dangerous situations. Since there have been so many security breaches in public spaces like airports, concerts, and other major gatherings, this is very helpful.

Rapid progress in areas like artificial intelligence [21], big data [22], and blockchain technology [15] has reshaped society and the range of skills accessible in the labor market. Socialization may also be taught in a classroom setting. People have to put in a lot of effort and time into collecting data using conventional ways, which makes it more challenging to converge and synchronize the generated art. These days, thanks to the Internet and the ever-improving state of information technology, people all over the world may quickly and easily get information on art and exhibitions in any part of the world. It is now possible for anyone, wherever in the world, to gather landscape data from all around the globe without ever leaving their living room.

2. Literature Review

As more and more people get access to powerful computers, online courses have become more popular. For instance, [5] discovered that elementary schools offered a more pleasant user experience when it came to online art education programs than museums did. [12] used the 2019 coronavirus infection (COVID-19) to highlight the value of online education and learning for students. Because to significant advancements in AI technology, much deep learning work has been done in fields such as speech and image identification. There have been several developments in emotion recognition tools, both for the human voice and for visual media. Using deep learning and a cognitive wireless framework, [9] created an audio-visual emotion detection system that can automatically interpret patients' sentiments inside an online medical framework. Results from the tests showed that the system made a useful contribution toward increasing people's ability to make use of healthcare information technology. Expanding on previous work, [11] summarize the relevant literature and apply deep learning techniques to the problem of identifying emotions in human voices. The writer ran a simulation of multi-modal emotion recognition and discovered that several forms of data input (such audio and video) may be integrated for greater efficacy.

[18] review the literature on automatic facial emotion recognition using deep learning. Better approaches for decoding and comprehending facial expressions [27] were shown to be necessary by researchers to enhance machine prediction. The results of his research show that deep learning approaches work well. [17] looked at the effectiveness of deep learning for intelligent face identification, comparing their results to those of the best existing deep models for facial recognition in Internet of Things (IoT) and cloud environments. The proposed model has been empirically shown to reach a precision of 98.65%. Verifying the efficacy of deep learning systems for medical image fusion As [15]. They found that by applying the deep learning model to the task of fusing images, processing times could be reduced and accuracy could be improved by the automated extraction of the input's most relevant features. Training accuracy may also be improved by expanding the size of the training data collection. Examine the use of deep learning for phenotypic image identification in plants [3]. For example, plant disease detection and species identification may be accomplished with the help of convolutional neural networks (CNNs), deep belief networks (DBNs), and recurrent neural networks (RNNs). By the end of the day, they determined that deep learning algorithms will play a significant role in the development of smart agriculture and big data going forward. Image identification of wind turbine blade damage was studied by [24], and they proposed a novel method for deep learning-based blade damage detection based on their findings. Their model integrates transfer learning and ensemble learning classifiers to improve accuracy. They used images of wind turbine blades to compare the proposed model's accuracy to that of SVMs, stand-alone deep learning models, and ensemble learning methods.

The authors of [20] modelled the connection between log-Mel and temporally modulated combined spectral regions while creating a Siamese neural network [28] for speech-based emotion identification via analogy learning. The results show that the suggested framework can function in non-steady-state settings, and that activation map layer-by-layer analysis can provide an explanation for the model's predictions. There have also been successes in studies examining emotion recognition and similarity measurement recognition techniques. For comparing skulls, for instance, [25] presented an SPCA-based technique. Facial micro expression analysis from video was proposed by [4]. To sum up, deep learning algorithms offer considerable practical usefulness in voice and picture recognition and have been the subject of much research in a variety of contexts, including speech-based image recognition.

3. Facial Available Databases

There are a variety of FER databases accessible to researchers for training the neuron network with examples, each with its own unique characteristics in terms of the amount and size of photos and videos, differences in lighting, population, and facial posture.

Table 1. Comparison between presented works.

Databases	Descriptions	Emotions
MultiPie (Gross et al., 2010)	More than 750,000 images captured by 15 view and 19 illumination conditions	Anger, Disgust, Neutral, Happy, Squint, Scream, Surprise

MMI (Pantic et al., 2005)	2900 videos, indicate the neutral, onset, apex and off-set	Six basic emotions and neutral
GEMEP FERA (Valstar et al., 2011)	289 images sequences	Anger, Fear, Sadness, Relief, Happy
SFEW (Dhall et al., 2011)	700 images with different ages, occlusion, illumination and head pose	Six basic emotions and neutral
CK+ (Lucey et al., 2010)	593 videos for posed and non-posed expressions	Six basic emotions, contempt and neutral
FER2013 (Goodfellow et al., 2013)	35,887 grayscale images collect from google image search	Six basic emotions and neutral
JAFFE (Lyons et al., 1998)	213 grayscale images posed by 10 Japanese females	Six basic emotions and neural
BU-3DFE (Lijun et al., 2006)	2500 3D facial images captured on two view -45°, +45°	Six basic emotions and neutral
CASME II (Yan et al., 2014)	247 micro-expressions sequences	Happy, Disgust, Surprise, Regression and others
Oulu-CASIA (Zhao et al., 2011)	2880 videos captured in three different illumination conditions	Six basic emotions
AffectNet (Mollahosseini et al., 2019)	More than 440.000 images collected from the internet	Six basic emotions and neutral
RAFD-DB (Li et al., 2017)	30000 images from real world	Six basic emotions and neutral
RaFD (Langner et al., 2010)	8040 images with different face poses, age, gender, sexes	Six basic emotions, contempt and neutral

Despite the remarkable performance of conventional face recognition algorithms using human feature extraction, researchers have shifted towards deep learning approaches over the last decade due to their strong machine identification capabilities. Here, we provide the most recent research results in FER, with a focus on the deep learning methods available for better identification. Training and testing databases should be used sequentially or in a static format. [19], proposed deep CNNs for FER by making use of the wide variety of available datasets. The picture was reduced in resolution to 48x48 pixels and facial landmarks were retrieved from the data. Afterwards, they relied on augmented data techniques. We use a 1x1 convolutional pooling layer, a 3x3 convolutional module, and a 5x5 convolutional module in a priming-style architecture. They may improve local performance by strategically placing convolutional layers inside the network, and they can reduce the overfitting problem by utilizing network techniques within the network.

To further understand how data preparation impacts sentiment categorization networks, Lopez and company conducted the aforementioned research. The data is improved, rotated, cropped, down sampled to 32x32 pixels, and intensity normalized before being fed into the convolutional neural network (CNN), which comprises of two convolutional pooling layers, the final two fully connected 256 and 7 neurons. The best weight from the practice phase is carried over to the real exam. The significance of this experience was determined by analyzing three open-source datasets (CK+, JAFFE, and BU-3DFE). The researchers showed that doing all of the preprocessing steps at once was more efficient than performing each one individually.

[10] proposed a new CNN architecture with sparse batch SBP normalization to solve the ballooning or vanishing gradient issue. To combat overfitting, a drop-off layer is placed between the first and third fully connected layers of the network. The network is characterized by its usage of two consecutive convolutional layers, followed by max pooling and SBP. To address the face occlusion problem, [23] propose a

novel CNN strategy that includes putting the data into a VGG network before using the CNN technique with an attention mechanism. The FED-RO, RAF-DB, and Affect Net databases are used to teach and test the framework.

In 2019, using the FER2013 database, [1] looked at how changing CNN parameters affected recognition accuracy. We started with a simple CNN consisting of two convolutional layers followed by a fully connected layer; the second convolutional layer played the A role for max pooling, and the third convolutional layer served as a SoftMax function for sorting [29]; all images were 64x64 pixels. As a consequence of these studies, two novel CNN models were built, with average accuracy values of 65.23 and 65.77 percent. These models are distinguished by the fact that they do not have fully-connected layer drops and maintain filters of constant size.

Two residual blocks, each with four convolutional layers, were suggested by [6] as the basis for a novel deep CNN. The images are cropped and their intensities are normalized during the preprocessing step, and then the model is trained using the JAFFE and CK+ databases. After looking at how facial expressions change over a range of emotions, [12]. proposed a CNN-LSTM hybrid architecture to analyze the collected data. A convolutional neural network (CNN) is used to learn the spatial features of the facial expressions across all emotional state frames, and then a long short-term memory (LSTM) is used to maintain the whole sequence. In addition, [26] proposed a novel architecture called Spatiotemporal Convolution with Nested LSTM (STC-NLSTM), which is built on three deep learning sub-networks: a 3DCNN for spatiotemporal feature extraction; a temporal T-LSTM that preserves temporal dynamics; and a convolutional C-LSTM to model multi-level features.

The accompanying graphic illustrates the many frameworks offered by the aforementioned academics, all of whom agree that fundamental emotions may be broken down into the following categories: joy, disgust, surprise, anger, fear, sorrow, and apathy.

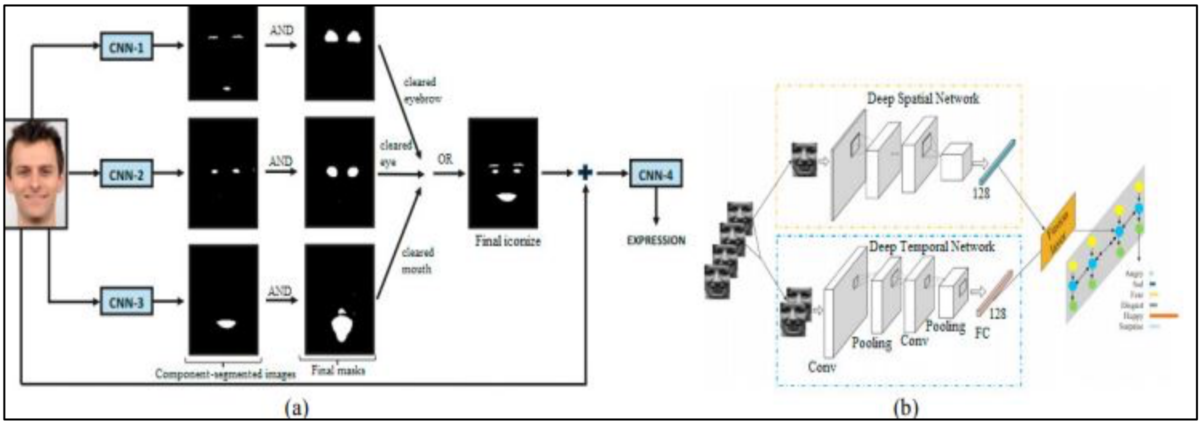

Figure 1. Frame work of convolutional neural networks.

4. Research Methodology

Ekman and Friesen's categorization of fundamental emotions was used as the basis for the classification of facial expressions into six distinct states: happiness, sorrow, surprise, fear, disgust, and rage. Furthermore, it broadens the scope of not one but two preexisting labels in the CK dataset: neutral and disdain. In this study, we employed convolutional neural networks (CNNs) to analyze facial expressions in order to identify eight distinct emotions. This range of feelings is shown in Figure 2 below.

Figure 2. Range of feelings used in dataset

Algorithm

The trained dataset folder is:

```
#dataset_directory=”C:\\users\\Aiza\\Desktop\\D\\kdef”
dataset_directory=”C:\\users\\Zunaira\\Desktop\\D\\kdef”
dataset_folder=os.listdir(dataset_directory)
```

It is cross platform library programmed using C++. It is used for face recognition and supports the face features using linear SVM.

```
#import required packages
  import cv2
  import dlib
Import argparse
import time

# handle command line arguments
ap = argparse.ArgumentParser()
ap.add_argument('-i'--image', required=True, help-'path to image file')
)
ap.add_argument('-w',--weights', default= ./mmod_human_Face_detector.dat',
help='path to weights files')
args = ap.parse_args ()
net = caffe.Net ("Models/VGG_FACE_deploy.prototxt", "Models/VGG_FACE. caffemodel",caffe.TEST)
def feature_extraction (single_frame) :
#net = caffe.Net ("Models/VGG_FACE_ deploy.prototxt", "Models/VGG_FACE. caffemodel",caffe,TEST
Input_image = single_frame
resized_image = caffe.io.resize_ image (input_image, [224,224])
```

open CV, sciPy, SVM and pickle: These are open-source library for computer vision, computation operations and emotion vectors. Imported library functions for python 3.5

```
import caffe
import scipy.io as sio
import numpy as np
import cv2
```

Main code for emotion extracted to train the classifier is given below

```
Def emotion_extraction (single frame):
#net = caffe.Net ("Models/VGG_ FACE deploy prototxt", "Models/VGG_FACE.caffemodel",
input image = single_frame
resized_image = caffe.io.resize_image (input_image, [224,224])
transformer = caffe.io.Transformer ( {' data' : net.blobs ['data' ] .data. shape })
transformer. set_transpose ('data', (2, 0, 1))
```

```
transtormer.set_channel_swap ('data',(2,1,0))
transformer. set _raw_scale ('data', 255)
net.blobs ['data:]. reshape (1, 3, 224, 224)
net.blobs ['data ]. Datal[...] = transformer.preprocess ('data', resized_ image)
net. forward ()
features = nec.blobs [' fc7 ].data [0] . reshape (l,4096)
return emotions
```

we employ the Expanded Cohn Kanade database (CK+ database) for our analysis. Ten thousand seven hundred and eight pictures representing 123 themes are available in CK+. It ranges from neutral to the extremes of surprise, joy, sadness, anger, contempt, and fear. Before the training phase begins, the dataset is preprocessed. In order to feed them into the CNN system, the photos are scaled down to 100x100.

To illustrate the suggested CNN architecture, Figure 3 is provided. It uses a four-layer architecture with two convolutional layers, two subsampling levels, and one output layer. The so-called c1 layer is the first convolutional layer and uses six masks. Subsampling occurs in the following layer, which itself consists of two layers (s1). There are 12 masks in the c2 layer, which stands for the second convolutional layer. Modern subsampling neural networks are two-layer structures. At the end, a completely linked layer is used to generate the classes.

The researcher tested various combinations of training and testing data sizes. We conducted our tests using all 10,708 photos from the CK+ database. The amounts of data we utilized for training and testing are displayed in Table 2. The root mean square error dramatically lowers with more training data, as shown experimentally. And whatever picture information is left behind once training is complete is known as test data. The RMS error shows a linear relationship with the number of samples used for testing. The MSE will be lower for smaller samples.

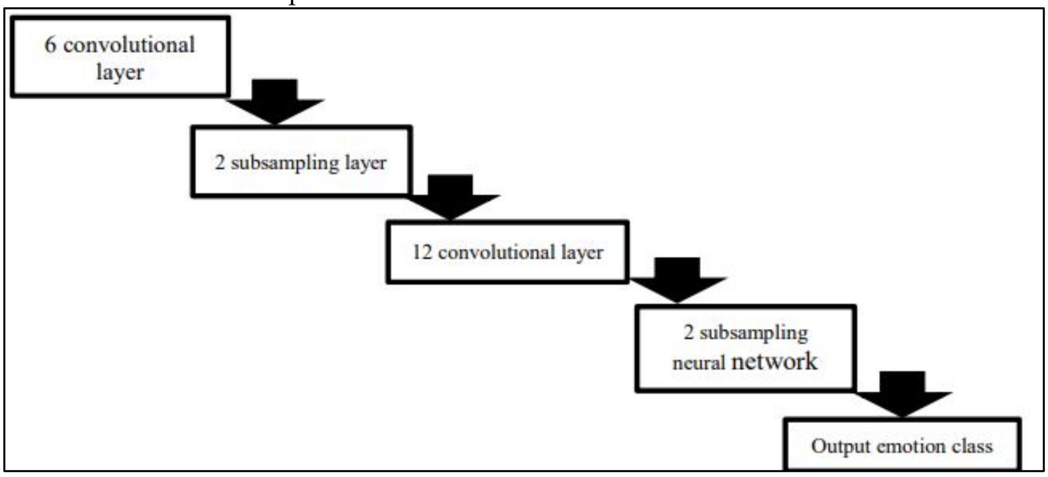

Figure 2. different steps adopted to train the model

We may compile a complete picture of the situation by gauging the data points using the appropriate data measurement instrument for each category. Anger registers an accuracy of 87.73 percent, disdain of 90.9 percent, disgust of 93.4 percent, fear of 91.7 percent, joy of 96.3 percent, sorrow of 91.1 percent, surprise of 98.0 percent, and apathy of 92.9 percent. There was a 92.81 percent rate of accuracy across the board.

Table 2. Experiment results

No	Num of training data	Num of testing data	MSE
1	8000	2708	0.6381
2	9000	1708	0.4614
3	10000	708	0.3729

5. Results

Results from experimental scenarios show that our system performs quite well, with an average accuracy of 92.81%. The surprise category has the highest accuracy at 98.09%, while the rage category has the lowest at 87.73%.

In this study, we examine and contrast the recent, substantial interest that scholars have demonstrated in FER via deep learning. The proposed model architecture is followed by emotion recognition in the automatic FER task. Data processing is also included. The preprocessing step, which was present in all of the articles cited in this study, included crucial elements such resized and cropped photos, normalization of spatial and intensity pixels, and data augmentation to increase the variety of the images and get rid of the over-fitting problem. Each of these techniques is clearly explained by [14] Several of the techniques and contributions discussed in this evaluation had high accuracy. [19] incorporated inception layers into the networks, which displayed substantial performance [23]. prefer to derive AU from the face rather than categorize emotions explicitly is considering looking into the occlusion image problem and deepening the network as [6] propose including the remaining blocks. These analysis highlights the benefits of training the network with iconized faces as opposed to only raw photos. [1] offer two brand-new CNN designs after completing a thorough analysis into the impact that the CNN's parameters have on the recognition rate. More than 90% of these tactics successfully delivered serious results. Researchers suggested a variety of deep learning structures for the extraction of spatio-temporal information, including a Deep CNN, 3DCNN, and CNN-LSTM combo. The approaches recommended by [23] are in line with the results attained. Greater precision is obtained by [12] method at a frequency greater than or equal to 100%. Researchers integrated CNN-RNN, notably the LSTM network, with spatial data when working with sequential data to attain high precision in FER. This implies that CNN is FER's primary deep learning network. We should also point out that in order to assess the effectiveness of the suggested neural network design, the researchers trained and tested their model across numerous databases. Table 2 shows that even when employing the same DL model across databases, the recognition rate varies. Table 2 summarizes all of the aforementioned articles and lists the architecture, database, and recognition rate.

6. Conclusion

A convolutional neural network structure is proposed by the researchers for recognizing facial expressions. Eight different expressions on the face are being studied for recognition. We train on varying amounts of data from the CK+ database, and find that the mean square error reduces with more data. The results show that the RMS error goes down as training data increases in size. There was also a 92.81% percentage of accuracy in the system's performance.

References

1. A. Agrawal et N. Mittal, « Using CNN for facial expression recognition: a study of the effects of kernel size and number of filters on accuracy », Vis. Comput., janv. 2019, doi: 10.1007/s00371-019-01630-9.
2. A. T. Lopes, E. de Aguiar, A. F. De Souza, et T. Oliveira-Santos, « Facial expression recognition with Convolutional Neural Networks: Coping with few data and the training sample order », Pattern Recognin., vol. 61, p. 610 628, janv. 2017, doi: 10.1016/j.patcog.2016.07.026.
3. A. Gudi, H. E. Tasli, T. M. Den Uyl, and A. Maroulis, "Deep Learning based FACS Action Unit Occurrence and Intensity Estimation," vol. 2013, 2015.
4. Ben, X., Ren, Y., Zhang, J., Wang, S. J., Kpalma, K., Meng, W., et al. (2021). Video-based facial micro-expression analysis: a survey of datasets, features and algorithms. IEEE Trans. Pattern Anal. Mach. Intel. doi: 10.1109/TPAMI.2021. 3067464.
5. Budur, T., Demir, A., and Cura, F. (2021). University readiness to online education during Covid-19 pandemic. Int. J. Soc. Sci. Educ. Stud. 8, 180–200. doi: 10.1504/ MEJM.2021.10033656.
6. Deepak, G., Teja, V., & Santhanavijayan, A. (2020). A novel firefly driven scheme for resume parsing and matching based on entity linking paradigm. Journal of Discrete Mathematical Sciences and Cryptography, 23(1), 157-165.
7. D. K. Jain, P. Shamsolmoali, et P. Sehdev, « Extended deep neural network for facial emotion recognition », Pattern Recognit. Lett., vol. 120, p. 69 74, avr. 2019, doi: 10.1016/j.patrec.2019.01.008.
8. D. H. Kim, W. J. Baddar, J. Jang, et Y. M. Ro, « Multi-Objective Based Spatio-Temporal Feature Representation Learning Robust to Expression Intensity Variations for Facial Expression Recognition », IEEE Trans. Affect. Comput., vol. 10, no 2, p. 223 236, avr. 2019, doi: 10.1109/TAFFC.2017.2695999.
9. Hossain, M. S., and Muhammad, G. (2019). An audio-visual emotion recognition system using deep learning fusion for a cognitive wireless framework. IEEE Wire. Commun. 26, 62–68. doi: 10.1109/MWC.2019.1800419.
10. J. Cai, O. Chang, X. Tang, C. Xue, et C. Wei, « Facial Expression Recognition Method Based on Sparse Batch Normalization CNN », in 2018 37th Chinese Control Conference (CCC), juill. 2018, p. 9608 9613, doi: 10.23919/ChiCC.2018.8483567.
11. Khalil, R. A., Jones, E., Babar, M. I., Jan, T., Zafar, M. H., and Alhussain, T. (2019). Speech emotion recognition using deep learning techniques: a review. IEEE Access 7, 117327–117345. doi: 10.1109/ACCESS.2019.2936124.
12. Kim, N. Y., and Kim, S. I. (2021). A study on user experience of online education programs with elementary schools and art museums in non-face-to-face era. J. Digit. Converge. 19, 311–317.
13. Li, S. Z., Jain, A. K., Tian, Y. L., Kanade, T., & Cohn, J. F. (2005). Facial expression analysis. Handbook of face recognition, 247-275.
14. Lopes PM, Moreira CR, Perrella A, Antunes JL, Cavalcanti MG. 3D volume rendering maxillofacial analysis of angular measurements by multislice CT. Oral Surg Oral Med Oral Pathol Oral Radiol Endod 2008;105:224-30.
15. Lv, Z., Qiao, L., Hossain, M. S., and Choi, B. J. (2021a). Analysis of using blockchain to protect the privacy of drone big data. IEEE Newt. 35, 44–49. doi: 10.1109/ MNET.011.2000154.
16. Lv, Z., Qiao, L., Singh, A. K., and Wang, Q. (2021b). Fine-grained visual computing based on deep learning. ACM Trans. Multimed. Compute. Commun. Appl. 17, 1–19. doi: 10.1145/3418215.
17. Masud, M., Muhammad, G., Alhumyani, H., Alshamrani, S. S., Chihuahua, O., Ibrahim, S., et al. (2020). Deep learning-based intelligent face recognition in IoT-cloud environment. Compute. Common. 152, 215–222. doi: 10.1016/j. comcom.2020.01.050.
18. Mellouk, W., and Handouzi, W. (2020). Facial emotion recognition using deep learning: review and insights. Procedia Compute. Sci. 175, 689–694. doi: 10.1016/ j. procs.2020.07.
19. A. Mollahosseini, D. Chan, et M. H. Mahoor, « Going deeper in facial expression recognition using deep neural networks », in 2016 IEEE Winter Conference on Applications of Computer Vision (WACV), mars 2016, p. 1 10, doi: 10.1109/WACV.2016.7477450
20. Ntalampiras, S. (2021). Speech emotion recognition via learning analogies. Pattern Recogn. Lett. 144, 21–26. doi: 10.1016/j.patrec.2021.01.018.
21. Ustun, T. S., Hussain, S. S., Yavuz, L., and Onen, A. (2021). Artificial Intelligence Based Intrusion Detection System for IEC 61850 Sampled Values Under Symmetric and Asymmetric Faults. IEEE Access 9, 56486–56495.
22. Wang, J., Yang, Y., Wang, T., Sherratt, R. S., and Zhang, J. (2020). Big data service architecture: a survey. J. Internet Technol. 21, 393–405. doi: 10.1201/ 9780429445552-50.
23. Y. Li, J. Zeng, S. Shan, et X. Chen, « Occlusion Aware Facial Expression Recognition Using CNN With Attention Mechanism », IEEE Trans. Image Process., vol. 28, no 5, p. 2439 2450, mai 2019, doi: 10.1109/TIP.2018.2886767.
24. Yang, X., Zhang, Y., Lv, W., and Wang, D. (2021). Image recognition of wind turbine blade damage based on a deep learning model with transfer learning and an ensemble learning classifier. Renew. Energy 163, 386–397. doi: 10.1016/ j. renene.2020.08.125.
25. Zheng, X., Zhao, J., and Lv, Z. (2020). Skull similarity comparison based on SPCA. Multimed. Tools Appl. 79, 22423–22446. doi: 10.1007/s11042-020-08937-z.
26. Z. Yu, G. Liu, Q. Liu, et J. Deng, « Spatio-temporal convolutional features with nested LSTM for facial expression recognition », Neurocomputing, vol. 317, p. 50 57, nov. 2018, doi: 10.1016/j.neucom.2018.07.028.
27. Iqbal, N., Saad Missen, M. M., Salamat, N., & Prasath, V. B. (2019). On Video Based Human Abnormal Activity Detection with Histogram of Oriented Gradients. In Handbook of Multimedia Information Security: Techniques and Applications (pp. 431-448). Springer, Cham.

28. Kajla, N. I., Missen, M. M. S., Luqman, M. M., & Coustaty, M. (2021). Graph neural networks using local descriptions in attributed graphs: an application to symbol recognition and hand written character recognition. IEEE Access, 9, 99103-99111.
29. Kajla, N. I., Missen, M. M. S., Luqman, M. M., Coustaty, M., Mehmood, A., & Choi, G. S. (2020). Additive Angular Margin Loss in Deep Graph Neural Network Classifier for Learning Graph Edit Distance. IEEE Access, 8, 201752-201761