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Procedia Computer Science 218 (2023) 2795–2805

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Machine Learning and Data Engineering

Fusion Fuzzy Logic and Deep Learning for Depression Detection Using Facial Expressions

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Abstract

One of the critical issues in detecting depression is using facial expressions with image data classification. In This research paper, we proposed Fusion Fuzzy Logic((FFL) with deep learning for identifying depressed people based on their facial expressions. Our proposed model the based on an advanced fuzzy algorithm with deep learning for unordered fuzzy rule(FR) initiation to offer appropriate and suitable opinions based on depressed people's facial expressions(FE), to allow Depression Recognition(DR) from image files and recorded video files. The primary goal of this research work was to use the fusion method to turn these facial expressions (FE) into the detection of depressed states. To elevate the performance of the Fusion Fuzzy Logic((FFL) (fuzzy logic and CNN)), delivering them entreated them several times to imitate specific facial expressions. Our proposed FFL with the CNN model produces exact and dependable results with a 94.3% overall accuracy comparable to human recognition.

Keywords: Fuzzy Logic, Convolutional Neural Network, Facial Expressions, Depression Detection

10.1016/j.procs.2023.01.251

1. Introduction

In normal social interaction, facial expression (FE) is the most powerful, simple, and straightforward tool to express emotion. People handle emotional input and exchange behaviors based on recognizing others' facial expressions (FE) [1], which has a significant evolutionary benefit for humans. According to cognitive theories (CT) of, depression is associated with negative schema about the individual, external events, and contexts. Depressed people, in particular, are said to be hyperaware of negative information and desire continual negative responses during social interactions. Therefore, it's widely considered that sad people have abnormal facial expression recognition patterns. At the moment, there are a variety of machine learning models for extracting image, text, video, and audio features for detecting depression (DD) levels in speech and facial movements. Fuzzy logic (FL) considers all subsequent frames equally as a histogram extraction approach, and the TOP frame ignores the unequally distributed remaining features in temporal space.to use the fuzzy logic and CNN (Convolutional neural network) [2] network to extract a temporal sequence representation of the spoken amplitude spectrum with multiple frames to show that the effects of different audio/video pictures on depression detection aren't exactly the same. The CNN+ Fuzzy structure processes a video segment with multiple consecutive video frames. The following is the CNN+ Fuzzy training Model: Video frames are used to self-teach the 3D CNN [3]. Then, by putting each video segment frame into the 3D CNN, we use the frame function to output the final complete connection layer. We describe a Fusion Fuzzy Logic ((FFL) logically based technique that uses the attention mechanism to highlight audio and video frames that effectively identify melancholy [3] and incorporate this spatial feature into time sequence representation. In this study, the fusion technique is used to aggregate CNN+ Fuzzy Logic allowing for the summarization of changes in each dimension of the segmental features. To the best of our ability, we provide a logic-based CNN+ Fuzzy [4] approach. The attention mechanism is used in this method to extract more information from various multimodal representation quality improvement methodologies [5]. A defined network architecture focuses on introducing a new fuzzy layer that can be injected straight into the Deep learning design. Moderately, we look at various use cases for the fuzzy layers at different points in the network design. For comparison, the fuzzy layers are used in the semantic segmentation [6] network's down-sampling (convolution network), up-sampling (deconvolution network), or both parts. To ensure consistency throughout our investigation, we adopted an FFL network design in which the only modification was adding or removing one or more fuzzy layers. introduces a deep learning architecture for accurately predicting depression levels through distribution learning. Specifically, it optimizes the distribution's expected values so that they get closer to the ground-truth values, based on a new expectation function that allows for the estimation of the underlying data distribution over depression levels. Even in the presence of label uncertainty, the proposed method is able to generate reliable predictions of depressive states. The following is how the rest of the paper is organized: The work at hand is examined related work in the second section. Our proposed methodology is thoroughly discussed in Section 3. The experimental results and discussion are presented in Section 4. Section 5 discussion, as well as a conclusion and Future work.

2. Related Work

M. Silvana et al. [7] explain that a system assists people in identifying mental illness by detecting diagnoses. The Fuzzy Logic method, in the form of an automation system, can be used to perform diagnostics. This system has the option of categorizing the symptoms of mental illness. Z. Zhang et al. [8] present a neuro-fuzzy approach classification algorithm that uses a weighted Fuzzy Network to distinguish depressed patients from controls based on 2-time domain and 4-frequency HRV domain characteristics. A. E. Yankovskaya et al. [9] the smart hybrid system was the name given to this type of smart system. The recognition of test patterns, discrete math, particular, fugitive classifications, and cognitive instruments are examples of smart system fundamentals. G. Shanmugasundaram et al. [10]. Researchers discovered that stress levels could be identified and validated using heart rate, moisture response, temperature response, and Fuzzy Logic. Mohammadi Motlagh et al. [11] the proposed system appears to benefit everyone, from ordinary people to medical professionals. Students of psychology can also be useful in the field of diagnostic reasoning. Atole S., et al. [12] This research aims to Dominant rotated local binary pattern (DRLBP) chosen for the face recognition algorithmic program thanks to its quick recognition method and less sensitiveness to noise and interference. Machanje D et al. [13] This paper focuses on the 2D approach, a new approach for detecting distress using a fluid K-NN classification model. Rather than using a single emotion to represent distress, such as fear, worry, or rage, the 2D technique uses two classification phases: the first assesses the level of excitement in speech, and the second checks the polarity of speech (negative or positive).

Table 1: Depression Detection with Facial Expressions

S.No.	Study	Major Highlight	Deep Learning Technique
1.	Rodrigues Makiuchi, M. et al.[14]	Used multi-fusion model for detection of depression.	BERT and Convolutional Neural Network.
2.	Lam, G. et al., [15]	Described the use of feature extraction from audio, video dataset.	tional Neural Network
3.	Lin, C. et al., [16]	Used Natural Language Processing (NLP) for extraction of dataset contains tweets.	BERT
4.	Zhang, X. et al., [17]	Depression detection take place using EEG signals.	Artificial Neural Network (ANN)
5.	Hou, Jie et al..[18]	emotional levels have been successfully classified	deep learning-based human emotion detection framework (DL-HEDF)
6.	Ghansah, Benjamin et al. [19]	Effectively capture the embedded discriminative informatio	Convolutional locality-sensitive Dictionary Learning (CLSDL)
7	Hata, Toshiyuki, et al. [20]	Artificial intelligence recognition of fetal facial expressions	Artificial Intelligence Deep Learning

3. Proposed Methodology

By studying the facial behaviors of humans using the Fuzzy Logic and CNN, we proposed FFL for evaluating depression [18] and stress levels. As a result, we set out to create a moderate, with good accuracy that health practitioners may use to diagnose and track the severity of the three depression states. Fuzzy Min-Max using a slow min-max procedure with the CNN Depressed People Pattern Classification technique. As a result, the input/output data set is partitioned into four subsets: training, rule extraction, rule selection, and testing, rather than two subsets (testing and training) [19]-[21] as in the original CNN. After that, the CNN layers are created and pruned according to a user-defined threshold. In the proposed chronological Fusion Fuzzy Logic + Fuzzy logic, the data set is used to generate the corresponding CNN layers. We determine the Time intervals to construct CNN sets and fuzzy sets in this paradigm. The network's rules, which comprise CNN layers with fuzzy sets, are established using FFL with Deep Learning [22]-[24]. In addition, the data set is evaluated in two passes, with the existing model classes refined in between. It can also create additional pattern classes as needed using the user interface. FFL-DL learning comprises a sequence of expansion and contraction processes to improve CNN's decision-making capabilities between classes. When there are overlapping CNN layers from various classes in the input space, contractions are used to remove overlapping regions, as in CNN+ Fuzzy. There are four layers of nodes in the FFL-DL learning structure. The input layer is the first one. There are exactly as many input nodes as there are input pattern dimensions. The CNN layer is the second layer. The number of hidden nodes is the same as the number of nodes in the input layers. The other hidden layer of the CNN is the last layer. Each node in the third hidden layer is represented by a fluffy temporal set. Forth layer is a fuzzy layer. The transmission functions of the nodes in the hidden layers are used to modify the membership functions. In matrices V and W, the least and maximum points are recorded [25]-[27], with V representing the start and W representing the end. While a soft decision is required, the decision threshold is kept as low as possible.

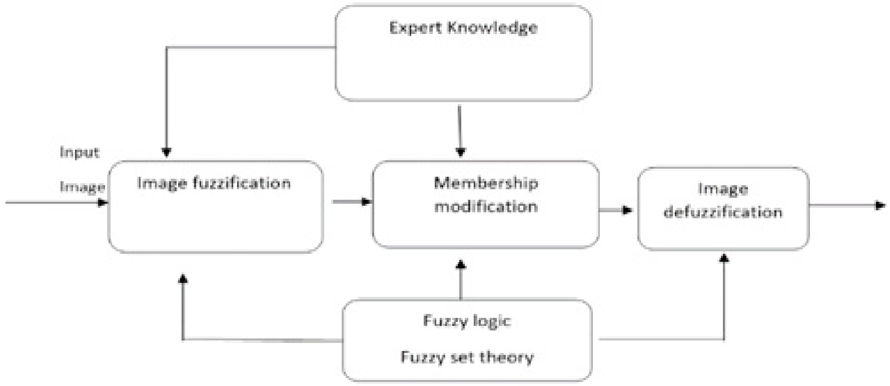

Figure 1: fuzzy approaches basic concepts

Vagueness and ambiguity can be effectively managed using fuzzy approaches (represent the image as a fuzzyset) In the form of fuzzy if-then rules, A powerful technique for describing and analyzing human knowledge is fuzzy logic. Both indicate a change in intensity. Compared to additive noise, edges usually have a lot of variance between neighboring pixels. Use directional gradients to capture these variations.

∇_N (a,b) = I(a,b-1) –I(a,b) …….(1)

Table 2: Find the fuzzy directional derivative in each direction.

NW	N	NE
W	(a,b)	E
SW	S	SE

To calculate the fuzzy directional derivative, we utilize eight criteria to distinguish noise from edges for each direction.

If (($\nabla_{NW}(a, b) is\ small\ and\ \nabla_{NW}$) (a-1),(b+1) is small) …………..(2)

If (($\nabla_{NW}(a, b) is\ small\ and\ \nabla_{NW}$) (a+1),(b-1) is small) …………..(3)

If (($\nabla_{NW}(a - 1, b + 1) is\ small\ and\ \nabla_{NW}$) (a+1), (b-1) is small) …. (4)

Then ∇_{NW}^{F} (a,b) is small

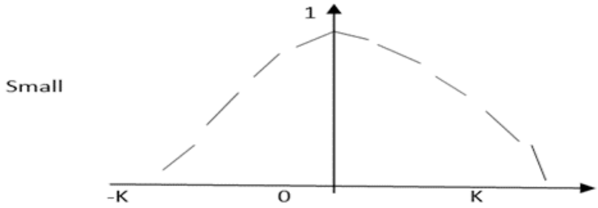

Figure 2: Filtering and smoothing

if ∇_{NW}^{F} (a,b) is small and ∇_{NW} (a,b) is positive, then c is positive
if ∇_{NW}^{F} (a,b) is small and ∇_{NW} (a,b) is negative then c is negative
Using these, we calculate the correction term

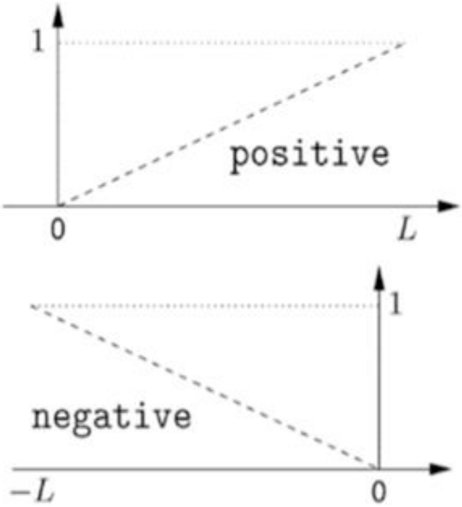

Figure 3: define the range

Step 1: Define the membership function

$$\mu_{pq} = \mathrm{G}(g_{pq}) = \left[1 + \frac{g_{max-}g_{pq}}{F_d}\right]^{-F_e} \text{……………………..…(5)}$$

Step 2: Modify the membership values

$$\mu_{pq} = \left[2.\left[\mu_{pq}\right]^2\right] \quad 0 \le \mu_{pq} \le 0.5 \text{………………………..…(6)}$$
$$0.5 \le \mu_{pq} \le 1$$

Step 3: Generate new gray-levels

$$g_{pq} = G^{-1}\,(\mu_{pq}) = g_{max}\text{- } F_d\,(\mu\_mn\,)^{\frac{-1}{Fe-1}} \text{ ………………… (7)}$$

Step 4: Configure the inference system's parameters
Step 5: The actual pixel is fuzzified
Step 6: Make an inference, such as if it's dark, it's darker, if it's grey, it's grayer, and if it's light, it's brighter.
Step 7: The inference result is defuzzified.

We used the Deep learning [28] with Fuzzy layer network architecture proposed in [6] as a model in this work. The key change is that six are used instead of five feature maps in a second layer. Figure 4 depicts the general functional scheme of CNN. Images of identifiable depression [29] people's body movements, images and videos are sent to the input layer.

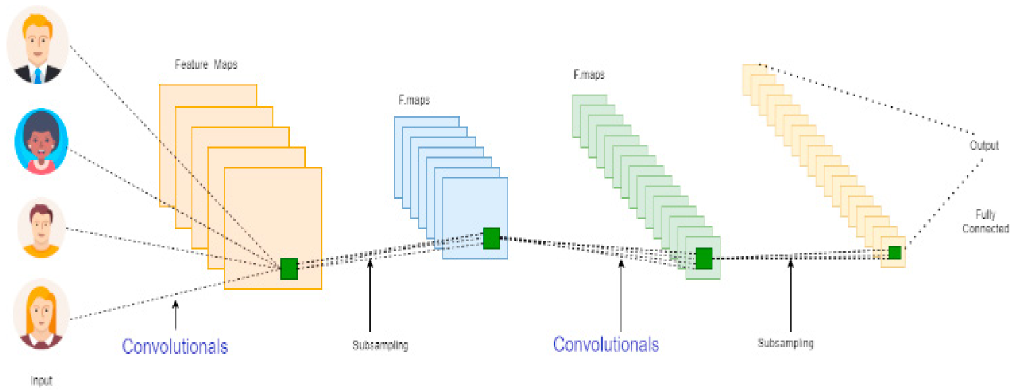

Figure 4: Depression Detection With Facial Expressions using CNN with Fuzzy logic

After that, a layer of six 20 x 20 convolutional feature maps is added. The receptive field on an input image is associated with each map element. There is also a convolutional layer with 80 maps of size 10 x 10 that has been added. The next layer has 200 neurons and is fully linked. The weight values of convolutional neurons in a single convolution layer are pooled, and the local feature's position is less essential. Shift variation can be obtained in this approach. The n-th feature map of the convolutional layer l's output neural values l Yn can be derived as follows:

$$B_n^l(a,b) = f\left(\sum_{pP_q^i} \sum_{i=0}^{K^l-1} \sum_{j=0}^{K^l-1} \omega_{pq}^l(i,j).Y_p^{l-1}(a+i, y+i) + bise_q^i\right)\text{.......(8)}$$

$$f(z) = A.\tanh\,(Sz)\ \text{........(9)}$$

while z is an input value matching to the activation value of a neuron, and A and S are parameters of the neuron. the purpose. The constants A = 1.7159 and S = 2/3 are proposed in the paper [3]. To tune the neural network, this study uses the usual back-propagation approach. Established of feature vectors of layer l–1 that are linked to the nth feature map of layer l; l mn is the synaptic coefficients matrix (convolution kernel); The size of the convolutional layer of the l-th layer's neurons is K l, and the bias factor for the l-th layer's neurons is l bn. scaled hyperbolic tangential is used as the neural network's activation function f(z): If a problematic judgment must be made, the procedure is extended by defining the output layer node's maximum value and threshold. The CNN+ Fuzzy logic model provides a 0 to 1 range in all dimensions. As a result, the unit cube represents pattern spaces in n dimensions (In). The membership functions of a ReLU are described in terms of temporal minimums and maximums. The hyper box level of a pattern is described. A fully included model in the ReLU is designated as a '1' member. Figure 5 shows the Flow diagram for working FFL Temporarily, fuzzy extraction Regulations for Depressed People's Identification: Each CNN classifier [30] is reduced to a single fugitive temporal rule using IF-THEN for rule extraction. During the interval [t1, t2], the rule extraction operation begins by quantifying each input function's minimum and maximum values. The interval [t1 t2] is divided into q intervals for quantization, with t2 – t1 = Q, and the input feature is equal to '1' at each endpoint depending on that characteristic.

$$\text{J(X,U,C)} = \sum_{i=1}^{i} \sum_{j=1}^{n} h(u_{ij})\, d_{ij}^{2} \ \text{...............(10)}$$

$$\text{J(X,U,C)} = \sum_{i=1}^{I} \sum_{j=1}^{n} u_{ij}\, d_{ij}^{2} + \gamma \sum_{i=1}^{i} \sum_{j=1}^{n} f(u_{ij})\text{...........(11)}$$

Rule of thumb for firing: The rule base is where the rules derived from the training phase are saved. Rules are chosen and applied throughout the testing step to produce good decisions using forward chain inference. Fugitive time limitations in rule harmonization, resulting in precise medical data set findings. During the testing phase, rule execution will be performed to monitor the input data properly.

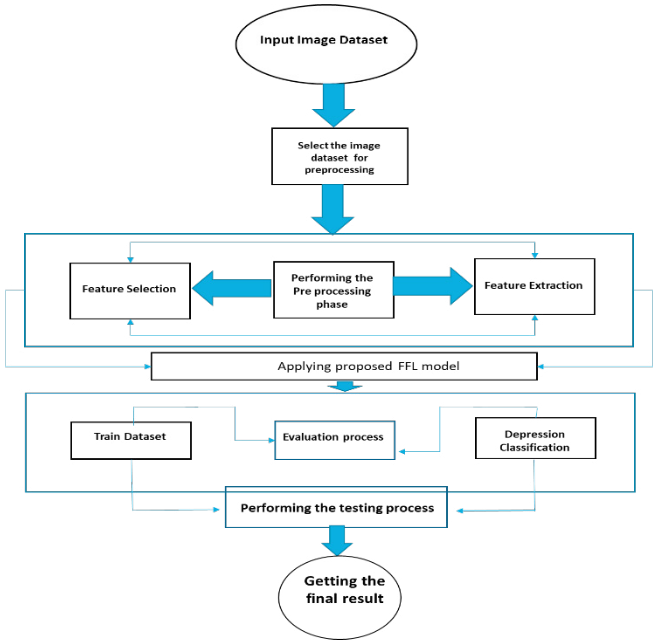

Figure 5: Flow diagram for working of FFL

4. Results analysis

Tensor flow, along with the other packages that were critically important to the operation, was utilised in the process of modelling the simulation of the analysis. Tensorflow is a Python-based framework that was developed by Google. This is an open-source framework that is readily available to the public and can function as a library.Comparing previous works on comparing with our approach to previous work, the level of depression on the AVEC 2013 [25], AVEC 2014 [28], [29], AVEC 2017 [30] and other researchers [32]-[36] data databases in this section is predicted. These comparisons are shown in Tables 4 and 5. We can see from them that our method performs well in identifying depressed people. The proposed FFL with CNN network integrates [31] spatiotemporally to achieve good performance and emphasizes frameworks related to depression detection. Based on a comparison of the AVEC 2017 (L. Yang et al., 2017) test set for our method with earlier work. The letters "A" and "V" stand for audio and video modes, respectively. A+V stands for audio and video modalities combined. The character '/' denotes that now the output will still not be produced.

The RMSE, MSE, and MAE are compared. The percentage error (percent error), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error is all performance criteria for picture categorization (MAPE). The following are the corresponding calculation methods:

$$\%Err = |y_i - \overline{y_i}|/y_i \times 100 \text{ .... } (12)$$

$$MSE = 1/N \sum_{i=1}^{N} (y^x - y)^2 \text{ ....}(13)$$

$$RMSE = \sqrt{1/n \sum_{i=1}^{N} (y^x - y)^2} \text{ ....}(14)$$

$$MAPE= {}^{100}/_{N}\, x \int_{i=1}^{N} \left| {}^{y - y^{x}}/_{y} \right| \ldots\ldots(15)$$

Table 3: Datasets for depression detection systems

Dataset	Modality	Depression Annotation
AVEC 2013 (Zhu et al., 2017) [25]	A + V	BDI-II (300 videos) (3ideos)
AVEC 2014 (Valstar et al., 2014) [28] (Jan et al., 2017) [29]	A + V	BDI-II
AVEC 2017 (L. Yang et al., 2017) [30]	A + V	BDI-II
Crisis Text Line	T	Manual annotation for depression
Dementia Bank Database	A + T + V	PHQ 8 (65,024 forum posts)
DAIC	A + T + V	HAMD

Table 4: Comparison of results based on a different dataset.

Modalities	Methods	Root Mean Square Error (RMSE)	Mean absolute error (MAE)
Image	CNN+Fuzzy logic model	8.49	6.16
	CNN	9.40	6.32
	Fuzzy logic	11.43	9.34
Audio	CNN+Fuzzy logic model	7.87	6.34
	CNN	9.43	7.55
	Fuzzy logic	10.25	8.33
Video	CNN+Fuzzy logic model	8.32	7.11
	CNN	9.99	7.89
	Fuzzy logic	9.34	7.52
Audio+ Video	CNN+Fuzzy logic model	8.32	6.54
	CNN	11.43	9.24
	Fuzzy logic	10.91	8.43

Table 5: Comparison of results based on different machine learning algorithms.

S.No.	Machine Learning Algorithm	AI-Based Method	Non AI-Based Based Method
1	CNN+ Fuzzy logic model	Accuracy: 94.3%, F1-score: 0.931	Accuracy: 73.3%, F1 Score: 0.692
2.	CNN	Accuracy: 91.3%, F1-score: 0.854	Accuracy: 85.3%, F1 Score: 0.740
3	BCNN	Accuracy: 85.40%, F1-score: 0.734	Accuracy: 50.3%, F1 Score: 0.740
4	Fuzzy logic	Accuracy: 78.66%, F1-score: 0.552	Accuracy: 46.3%, F1 Score:0.453

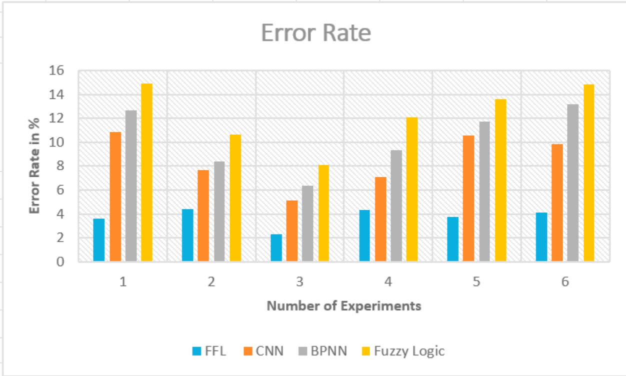

Figure 6: Comparative analysis FFL, CNN , BPNN, Fuzzy Logics

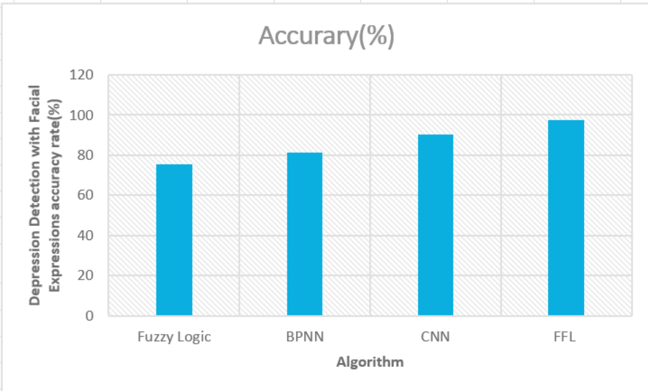

Figure 7 : Depression Detection with Facial Expressions

It is more appropriate than other methods of pooling for each segment-level dimension. It is because of statistical variables (mean, median, etc.). The order of functions used in [22] when creating a dictionary In FV encoding is ignored. The AVEC2013 database's study attempts to increase detection accuracy. To that purpose, in AVEC2013 and AVEC 2017 (L. Yang et al., 2017), we revisited our work on anticipating depression levels. Previous studies were compared to the AVEC 2017 (L. Yang et al., 2017) test set. The letters "A" and "V" stand for audio and video modes, respectively. The audio and visual modalities are combined in A+V. The concatenation of features extracted by our approach from two 'Northwind' and 'FreeForm' tasks is referred to as 'Ours with Con.' The character '/' denotes that the result will not be produced. Insufficient visual behaviors (such as facial texture extraction, FAO, landmark, head positions, and gazes). Furthermore, the division of numerous facial parts improves the performance of the works. The method is the most effective since it examines facial gestures throughout the full video rather than splitting it up into chunks. Our technique produces the best projection results for multimodal fusion, especially when combined with other tasks from the AVEC 2017 (L. Yang et al., 2017) database. This is because when additional information is captured between modalities, the concatenation of audio and video features in or linear combinations of decisions is weak. Unlike these, the proposed CNN+Fuzzy logic model strategy improves multimodal representation quality by utilizing. In this section, we analyze the results for the Fuzzy logic model in which we have used CNN and the Combination of CNN+ Fuzzy logic algorithm for the dataset based on the questionnaire asked to students based on the test. The research paper contains a set of questions based on the learning practices during AI-based methods and simple methods. In the Table 5, analysis of above-mentioned algorithms using several parameters. CNN+ Fuzzy logic model is the best performer with accuracy 94.3% and F1-score as 0.931. In converse, the best accuracy showed in the CNN method for youth is 85.3% and F1-score equal to 0.740. Thus, Table 5 shows that AI-based methods are more efficient than other methods.

5. Conclusion

Depressed people can be identified on several of different parameters. Some differences in speech, video, and facial activities have been discovered using Fuzzy Logic studies between depressed and healthy people. We propose a spatiotemporal representation framework of the CNN+ Fuzzy logic model for automatically detecting depression levels. The proposed FFL with a deep learning network emphasizes the depression detection model and integrates spatial and temporal information. Furthermore, by extracting additional information from modalities, the proposed Fuzzy logic strategy improves the quality of multimodal representation. Our approach performs well in terms of detection performance with experimental results on AVEC 2014 and AVEC 2017. Monitoring the levels of stress and anxiety that patients and elderly people experience on a daily basis can be accomplished through the use of emotion detection as a monitoring tool. We will segment the combined form of data sets, which provides a synchronous response in feature extraction. Furthermore, when the data is available, we intend to use this framework to detect symptoms of other diseases with an identical dataset.

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