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A Comprehensive Investigation on Emotional Detection in Deep Learning

Anand M[1], Dr. S. Babu[2]
[1]Research Scholar, Department of Computing Technologies, SRM Institute of Science & Technology, Kattankulathur, Tamil Nadu, India
[2]Associate Professor, Department of Computing Technologies, SRM Institute of Science & Technology, Kattankulathur, Tamil Nadu, India

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ABSTRACT

Emotion recognition is a substantial problem in the field of Big Data. In a wide range of applications, reliable categorization, analysis, and interpretation of emotional content is greatly desired. In this paper, we look at how Deep Learning models perform on an emotion perception test. Facial Expression Recognition (FER) plays an important role in machine learning tasks. Deep Learning models do well in FER tasks, but they lack explanation for their conclusions. Based on the notion that facial expression is a mixture of facial muscle movements, we discover a link between Facial Action Coding Units (AUs) and Emotion label in the CK+ Dataset. In this study, we offer a model that uses AUs to explain the classification outcomes of a Convolutional Neural Network (CNN) model. The CNN model is trained using the CK+ Dataset and identifies emotions using extracted characteristics. The CNN model's retrieved features and emotion classes are used by the explanation model to classify multiple AUs. Explanation model creates AUs quite effectively with only characteristics and emotion classes acquired from the CNN model, according to our trial. Experimental research was constructed, and several deep learning approaches were tested using publically available datasets. The findings are highly intriguing, highlighting the benefits of each strategy and training style studied.
Keywords : Deep Learning, Emotional, Facial Expression

I. INTRODUCTION

To increase the use of deep learning models in crucial activities where human life is at stake, the deep learning model must be justified; it must explain the rationale for its choice. However, the existing deep learning model lacks this capability.

Facial Expression Recognition is one example that may be used to provide reasons for crucial jobs such as driver sleepiness detection. We represent face expression as a series of muscular movements. In other words, face expressions may be represented using combinations of atomic facial muscle movements. The automatic FER is the most investigated by researchers when compared to other modalities to statistics developed by Philipp et al.[6], but it is a difficult process since each individual expresses his or her emotion in a unique way. Several barriers and problems exist in this region that should not be overlooked, such as variations in head posture, brightness, age, gender, and backdrop, as well as the problem of occlusion produced by Sunglasses, scarf, skin illness...etc.

Traditional sentiment lexicon-based approaches for emotional categorization have significant drawbacks. For example, the appearance of new words will necessitate manually supplementing existing sentiment lexicons, and some emotional words in previous emotional lexicons are no longer the original meaning affected by the internet, posing a significant challenge to the method of using emotion lexicon to classify emotions. The majority of study employs the statistical natural language processing approach, although it is impossible to ensure semantic understanding of the text, resulting in a poor categorization effect. This research examines integrating the two approaches to categorize text emotions, utilizing the sentiment lexicon to increase semantic comprehension and then using CNN to classify the labelled dataset, hence boosting sentiment classification efficiency.

The Face Action Coding Technique is a system for mapping the motions of the facial muscles in the study of facial expression (FACS). FACS is a technique for categorizing human facial motions based on how they look on the face. With Action Units, FACS encodes the essential activities of individual muscles or groups of muscles (AUs).

We present a summary of recent improvements in perceiving emotions by identifying facial expressions using various deep learning architectures in this study. We provide new findings from 2016 to 2020, together with an analysis of the issues and contributions. It is structured as follows: Section two introduces several publicly available public databases, Section three presents a current state of the art on the FER utilizing deep learning, and Sections four and five conclude with a discussion and comparisons, followed by a general conclusion with future efforts.

In general, the comments on the e-commerce platform are divided into three sections: comment content, comment star, and comment date. The customer chooses the remark star, which represents the consumer's overall attitude. There may be certain instances where this is not the case. When a client is displeased with a certain component, such as logistics, but is content with other aspects, the customer gives one star, which stands for very dissatisfied. This circumstance decreases the analysis's accuracy. We began by crawling sections of comments on an e-commerce site. There are three types of reviews: favorable, middling, and negative. They can be used as a guide for categorization. The emotional content lexicon labels the substance of the comments, and the marked comment dataset is then processed through the CNN model.

II. RELATED WORKS

A. Sentiment classification:

Existing sentiment classification algorithms may be broadly classified into two types: those based on emotional semantic qualities and those based on statistical natural language processing . The emotional semantics characteristics technique refers to judging the text's emotional polarity using an emotional lexicon. The statistical natural language processing approach entails utilising labelled data to train the classifier and then using the learned classifier to identify the text. Other author categorises human emotions into six categories: anger, contempt, fear, joy, sadness, and surprise. Deep learning emotional classification accuracy of deep learning emotional classification.

B. Convolutional Neural Networks:

Existing sentiment classification algorithms may be broadly classified into two types: those based on emotional semantic qualities and those based on statistical natural language processing. The emotional semantics characteristics technique refers to judging the text's emotional polarity using an emotional lexicon.

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C. Database available for Emotional detection:

One of the key aspects of deep learning is training the neuron network with examples. Several FER databases are currently accessible to researchers to help them with this job, each one unique in terms of the amount and size of photos and videos, differences in lighting, population, and facial posture. Some are shown in Table.1, and we will notice their appearance in the works listed in the next section.

Table 1 : A summary of some FER databases

DATABASES	DESCRIPTIONS	EMOTIONS
Numerous	More than 750,000 images captured by 15 view and 19 illumination conditions	Angeer, Disgust, Neutral, Happy, Squint, Scream, Surprise
MMI	2900 videos, indicate the neutral, onset, apex and offset	Six basic emotions and neutral
GEMEP FERA	289 images sequences	Anger, Fear, Sadness, Relief, Happy
SFEW	700 images with different ages, occlusion, illumination and head pose.	Six basic emotions and neutral
CK+	593 videos for posed and non-posed expressions.	Six basic emotions, contempt and neutral
FER2013	35,887 grayscale images collect from google image search	Six basic emotions and neutral
JAFFE	213 grayscale images posted by 10 Japanese females	Six basic emotions and neutral
BU-3DFE	2500 3D facial images captured on two view - 45^0, $+45^0$	Happy, Disgust, Surprise, Regression and others
CASME II	247 micro expressions sequences	Six basic emotions
Oulu-CASIA	2880 video captured in three different illumination conditions	Six basic emotions and neutral
AffectNet	More than 440000 images collected from the internet	Six basic emotions and neutral
RAFD-DB	30000 images from real world	Six basic emotions, contempt and neutral

Facial emotion recognition using deep learning:

Despite the significant success of traditional face recognition approaches based on the extraction of handmade characteristics, researchers have gravitated toward the deep learning approach over the last decade due to its high automated detection capability.

In this regard, we will describe some new FER research that demonstrate proposed deep learning strategies for enhanced detection. Train and test on a variety of static and sequential databases.

Deep CNN is proposed by Mollahosseini et al. [23] for FER across multiple accessible databases. The photos were resized to 48x48 pixels after the face landmarks were extracted from the data. The augmentation data approach was then used. The architecture employed consists of two convolution-pooling layers, followed by two inception type modules with convolutional layers of sizes 1x1, 3x3, and 5x5. They demonstrate the ability to employ the network-in-network approach, which allows enhancing local performance owing to convolution layers applied locally, as well as reducing the over-fitting problem.

Mohammadpour et al. [25] used similar pre-processing approaches. They suggest an unique CNN for identifying AUs of the face. They employ two convolution layers for the network, each followed by a max pooling and concluding with two fully linked layers that represent the amount of activated AUs.

In 2019, Agrawal et Mittal [29] use the FER2013 database to investigate the effect of changing CNN parameters on recognition rate. For starters, all of the photos are 64x64 pixels in size, with varying numbers of filters. Also, the kind of optimizer used (adam, SGD, adadelta) on a basic CNN with two consecutive convolution layers, the second layer serving as the max pooling layer, and a softmax function for classification. According to these investigations, researchers created two innovative CNN models that reach an average accuracy of 65.23 percent and 65.77 percent. The difference between these models is that they do not feature completely connected layers dropout, and the same filter size stays in the network.

Kim et al. [31] investigate the fluctuation of facial expressions during emotional states and suggest a spatio-temporal architect based on a mix of CNN and LSTM. Initially, CNN learns the spatial aspects of the facial expression in all emotional state frames, followed by an LSTM that preserves the whole sequence of these spatial properties. Yu et al. [32] also present a novel architecture called Spatio-Temporal Convolutional with Nested LSTM (STC-NLSTM), which is based on three deep learning subnetworks: 3DCNN for extracting spatio-temporal features, temporal T-LSTM for preserving temporal dynamics, and convolutional C-LSTM for modelling multi-level features.

III. DISCUSSION AND COMPARISON

In this study, we clearly stated that academics have shown a strong interest in FER using deep learning in recent years. The automated FER job goes through several stages, including data processing, suggested model design, and emotion recognition.

Preprocessing is an important step that was present in all of the papers cited in this review, and it includes several techniques such as resized and cropped images to reduce training time, normalisation of spatial and intensity pixels, and data augmentation to increase image diversity and eliminate over-fitting. Llopes et al. [24] cover all of these strategies in detail.

Several of the methodologies and contributions provided in this evaluation were shown to be highly accurate. Mollahosseini et al. [23] shown the importance of adding inception layers to networks. Mohammadpour et al. [25] prefer to extract AU from the face rather than classifying emotions directly. Li et al. [27] are interested in studying the problem of occlusion pictures, and Deepak et al. [30] propose adding residual blocks to make the network deeper. Yolcu et al. [28] demonstrate the benefit of including an iconized face in the network's input, which improves performance when compared to training with only raw photos. Following an in-depth examination of the influence of CNN parameters on recognition rate, Agrawal et Mittal.[29] proposes two novel CNN architectures. The majority of these approaches produced competitive outcomes in excess of 90% of the time. Digital twin proposed by El Saddik [9] is the convergence of science and technology to improve well-being of citizens and quality of life. Digital twins are virtual representations of living or non-living physical entities by bridging the physical and the virtual world [43].

Researchers attain great precision in FER by using CNN networks with spatial data, and for sequential data, researchers employed a mix of CNN-RNN, particularly the LSTM network, indicating that CNN is the foundational network of deep learning for FER. The Softmax function and the Adam optimization technique are the most often employed CNN parameters by researchers. We also remark that, in order to evaluate the efficacy of the suggested neural network design, researchers trained and tested their model in many databases, and we plainly observe that the identification rate differs from one database to the next using the same DL model (See Table.2).

Table 2 summarizes all of the papers mentioned above, including the architecture, database, and recognition rate.

Table 2: Comparison between presented works.

Database	Architecture used	Recognition rate
Multipie, MMI, DISFA, FERA, SFEW, CK+,FERR2018	CNN	94.7%, 77.9%, 55%, 76.4%, 47%, 93.2%, 61%
CK+, JAFFE, BU-3DFE	CNN	96.76% for CK+
CK+	CNN	97.01%
RAF-DB	SBN- CNN	80.54%, 54.84%
RAFD	ACNN	94.44%
FER2018	CNN	65%
JAFFE, CK+	CNN	95.23%, 93.24%
Oulu-CASIA	DCBiLSTM	80.71%

IV. CONCLUSION AND FUTURE WORK

This study provided current research on FER, allowing us to stay up to date on the latest discoveries in this field. We have described various CNN and CNN-LSTM architectures recently proposed by different researchers, as well as presented some different databases containing spontaneous images collected in the real world and others formed in laboratories (SeeTable.1), in order to have and achieve an accurate detection of human emotions[41]. We also give a debate that demonstrates the high rate attained by researchers, which highlights that robots today will be increasingly capable of reading emotions, implying that human-machine contact will become more natural.

FER are one of the most essential methods of conveying information about an emotional state, but they are always restricted to learning only the six fundamental emotions plus neutral. It contrasts with what is present in everyday life, which contains more complicated emotions. This will encourage researchers to design larger databases and sophisticated deep learning architectures in the future to detect all fundamental and secondary emotions. Furthermore, emotion recognition has progressed from unimodal analysis to sophisticated multimodal systems. According to Pantic and Rothkrantz [36], multimodality is one of the conditions for having an optimum detection of human emotion. Researchers are currently focusing their efforts on developing and delivering strong multimodal deep learning architectures and databases, such as the audio-visual fusion examined by Zhang et al. [37] and Ringeval et al. [38] for audio-visual and physiological modalities.

V. REFERENCES

[1]. HAOPENG WANG, DIANA P. TOBÓN V, M. SHAMIM HOSSAIN, (Senior Member, IEEE), AND ABDULMOTALEB EL SADDIK "Deep

Learning (DL)-Enabled System for Emotional Big Data" VOLUME 9, 2021.

[2]. C.-N. Anagnostopoulos, T. Iliou, et I. Giannoukos, « Features and classifiers for emotion recognition from speech: a survey from 2000 to 2011 », Artif. Intell. Rev., vol. 43, no 2, p. 155-177, févr. 2015, doi: 10.1007/s10462-012-9368-5.

[3]. L. Shu et al., « A Review of Emotion Recognition Using Physiological Signals », Sensors, vol. 18, no 7, p. 2074, juill. 2018, doi: 10.3390/s18072074.

[4]. C. Marechal et al., « Survey on AI-Based Multimodal Methods for Emotion Detection », in High-Performance Modelling and Simulation for Big Data Applications: Selected Results of the COST Action IC1406 cHiPSet, J. Kołodziej et H. González-Vélez, Éd. Cham: Springer International Publishing, 2019, p. 307-324.

[5]. M. H. Alkawaz, D. Mohamad, A. H. Basori, et T. Saba, « Blend Shape Interpolation and FACS for Realistic Avatar », 3D Res., vol. 6, no 1, p. 6, janv. 2015, doi: 10.1007/s13319-015-0038-7.

[6]. P. V. Rouast, M. Adam, et R. Chiong, « Deep Learning for Human Affect Recognition: Insights and New Developments », IEEE Trans. Affect. Comput., p. 1-1, 2018, doi: 10.1109/TAFFC.2018.2890471.

[7]. C. Shan, S. Gong, et P. W. McOwan, « Facial expression recognition based on Local Binary Patterns: A comprehensive study », Image Vis. Comput., vol. 27, no 6, p. 803-816, mai 2009, doi: 10.1016/j.imavis.2008.08.005.

[8]. T. Jabid, M. H. Kabir, et O. Chae, « Robust Facial Expression Recognition Based on Local Directional Pattern », ETRI J., vol. 32, no 5, p. 784-794, 2010, doi: 10.4218/etrij.10.1510.0132.

[9]. S. Zhang, L. Li, et Z. Zhao, « Facial expression recognition based on Gabor wavelets and sparse representation », in 2012 IEEE 11th International Conference on Signal Processing, oct. 2012, vol. 2, p. 816-819, doi: 10.1109/ICoSP.2012.6491706.

[10]. R. Gross, I. Matthews, J. Cohn, T. Kanade, et S. Baker, « Multi-PIE », Proc. Int. Conf. Autom. Face Gesture Recognit. Int. Conf. Autom. Face Gesture Recognit., vol. 28, no 5, p. 807-813, mai 2010, doi: 10.1016/j.imavis.2009.08.002.

[11]. M. Pantic, M. Valstar, R. Rademaker, et L. Maat, « Web-based database for facial expression analysis », in 2005 IEEE International Conference on Multimedia and Expo, juill. 2005, p. 5 pp.-, doi: 10.1109/ICME.2005.1521424.

[12]. M. F. Valstar, B. Jiang, M. Mehu, M. Pantic, et K. Scherer, « The first facial expression recognition and analysis challenge », in Face and Gesture 2011, mars 2011, p. 921-926, doi: 10.1109/FG.2011.5771374.

[13]. A. Dhall, R. Goecke, S. Lucey, et T. Gedeon, « Static facial expression analysis in tough conditions: Data, evaluation protocol and benchmark », in 2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops), nov. 2011, p. 2106-2112, doi: 10.1109/ICCVW.2011.6130508.

[14]. P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, et I. Matthews, « The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression », in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, juin 2010, p. 94-101, doi: 10.1109/CVPRW.2010.5543262.

[15]. I. J. Goodfellow et al., « Challenges in Representation Learning: A Report on Three Machine Learning Contests », in Neural Information Processing, Berlin, Heidelberg, 2013, p. 117-124, doi: 10.1007/978-3-642 -42051-1_16.

[16]. M. Lyons, M. Kamachi, et J. Gyoba, « The Japanese Female Facial Expression (JAFFE) Database ». Zenodo, avr. 14, 1998, doi: 10.5281/zenodo.3451524.

[17]. Lijun Yin, Xiaozhou Wei, Yi Sun, Jun Wang, et M. J. Rosato, « A 3D facial expression database for facial behavior research », in 7th International Conference on Automatic Face and Gesture Recognition (FGR06), avr. 2006, p. 211-216, doi: 10.1109/FGR.2006.6.

[18]. W.-J. Yan et al., « CASME II: An Improved Spontaneous Micro-Expression Database and the

Baseline Evaluation », PLoS ONE, vol. 9, no 1, janv. 2014, doi: 10.1371/journal.pone.0086041.

[19]. G. Zhao, X. Huang, M. Taini, S. Z. Li, et M. Pietikäinen, « Facial expression recognition from near-infrared videos », Image Vis. Comput., vol. 29, no 9, p. 607-619, août 2011, doi: 10.1016/j.imavis.2011.07.002.

[20]. A. Mollahosseini, B. Hasani, et M. H. Mahoor, « AffectNet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild », IEEE Trans. Affect. Comput., vol. 10, no 1, p. 18-31, janv. 2019, doi: 10.1109/TAFFC.2017.2740923.

[21]. S. Li, W. Deng, et J. Du, « Reliable Crowdsourcing and Deep Locality-Preserving Learning for Expression Recognition in the Wild », 2017, p. 2852-2861.

[22]. O. Langner, R. Dotsch, G. Bijlstra, D. H. J. Wigboldus, S. T. Hawk, et A. van Knippenberg, « Presentation and validation of the Radboud Faces Database », Cogn. Emot., vol. 24, no 8, p. 1377-1388, déc. 2010, doi: 10.1080/02699930903485076.

[23]. 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.

[24]. 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 Recognit., vol. 61, p. 610-628, janv. 2017, doi: 10.1016/j.patcog.2016.07.026.

[25]. M. Mohammadpour, H. Khaliliardali, S. M. R. Hashemi, et M. M. AlyanNezhadi, « Facial emotion recognition using deep convolutional networks », in 2017 IEEE 4th International Conference on Knowledge-Based Engineering and Innovation (KBEI), déc. 2017, p. 0017-0021, doi: 10.1109/KBEI.2017.8324974.

[26]. 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.

[27]. 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.

[28]. G. Yolcu et al., « Facial expression recognition for monitoring neurological disorders based on convolutional neural network », Multimed. Tools Appl., vol. 78, no 22, p. 31581-31603, nov. 2019, doi: 10.1007/s11042-019-07959-6.

[29]. 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.

[30]. 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.

[31]. 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.

[32]. 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.

[33]. D. Liang, H. Liang, Z. Yu, et Y. Zhang, « Deep convolutional BiLSTM fusion network for facial expression recognition », Vis. Comput., vol. 36, no 3, p. 499-508, mars 2020, doi: 10.1007/s00371-019-01636-3.

[34]. S. M. Mavadati, M. H. Mahoor, K. Bartlett, P. Trinh, et J. F. Cohn, « DISFA: A Spontaneous Facial Action Intensity Database », IEEE Trans.

Affect. Comput., vol. 4, no 2, p. 151-160, avr. 2013, doi: 10.1109/T-AFFC.2013.4.

[35]. M. F. Valstar et al., « FERA 2015 - second Facial Expression Recognition and Analysis challenge », in 2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG), mai 2015, vol. 06, p. 1-8, doi: 10.1109/FG.2015.7284874.

[36]. M. Pantic et L. J. M. Rothkrantz, « Toward an affect-sensitive multimodal human-computer interaction », Proc. IEEE, vol. 91, no 9, p. 1370-1390, sept. 2003, doi: 10.1109/JPROC.2003.817122.

[37]. S. Zhang, S. Zhang, T. Huang, et W. Gao, « Multimodal Deep Convolutional Neural Network for Audio-Visual Emotion Recognition », in Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval, New York, NY, USA, 2016, p. 281–284, doi: 10 .1145/2911996.2912051.

[38]. F. Ringeval et al., « Prediction of asynchronous dimensional emotion ratings from audiovisual and physiological data », Pattern Recognit. Lett., vol. 66, p. 22-30, nov. 2015, doi: 10.1016/j.patrec.2014.11.007.

[39]. S. Srivastava, P. Gupta and P. Kumar, "Emotion Recognition Based Emoji Retrieval Using Deep Learning," 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), 2021, pp. 1182-1186, doi: 10.1109/ICOEI51242.2021.9452832.

[40]. R. R. Subramanian, C. S. Niharika, D. U. Rani, P. Pavani and K. P. L. Syamala, "Design and Evaluation of a Deep Learning Algorithm for Emotion Recognition," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), 2021, pp. 984-988, doi: 10.1109/ICICCS51141.2021.9432336.

[41]. A. Poulose, C. S. Reddy, J. H. Kim and D. S. Han, "Foreground Extraction Based Facial Emotion Recognition Using Deep Learning Xception Model," 2021 Twelfth International Conference on Ubiquitous and Future Networks (ICUFN), 2021, pp. 356-360, doi: 10.1109/ICUFN49451.2021.9528706.

[42]. H. Lee and K. Hong, "A study on emotion recognition method and its application using face image," 2017 International Conference on Information and Communication Technology Convergence (ICTC), 2017, pp. 370-372, doi: 10.1109/ICTC.2017.8191005.

[43]. N. Naik and M. A. Mehta, "Hand-over-Face Gesture based Facial Emotion Recognition using Deep Learning," 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), 2018, pp. 1-7, doi: 10.1109/ICCSDET.2018.8821186.

[44]. T. L. Praveena and N. V. M. Lakshmi, "Multi Label Classification for Emotion Analysis of Autism Spectrum Disorder Children using Deep Neural Networks," 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), 2021, pp. 1018-1022, doi: 10.1109/ICIRCA51532.2021.9545073.

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