

A SCORING SYSTEM FOR RESTAURANTS BASED ON DEEP LEARNING-BASED FACIAL EXPRESSION RECOGNITION

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ABSTRACT: The prevalence of automated & unmanned eateries has recently surged. The lack of personnel precludes direct insight into consumers' perceptions of their experiences using the restaurant concept. This research introduces a grading system using facial emotion detection via pre-trained convolutional neural network, or CNN, model. It consists of a downloaded Android mobile application, an internet server, and a pre-trained AI server. Both the cuisine and the ambiance have to be evaluated. The rating system now offers three expressions: pleased, neutral, and unhappy.

INTRODUCTION

Facial expression serves as a potent, innate, and universal indicator for individuals to communicate their emotional states and intents. A multitude of research has been undertaken on autonomous facial expression analysis due to its significant relevance in social robotics, medical interventions, driver fatigue monitoring, and several other human-computer interface systems. In the domain of computer vision and machine learning, several facial expression recognition (FER) methods have been investigated to encode expressive information from face representations. In the twentieth century, Ekman and Friesen [3] identified six fundamental emotions via cross-cultural research [4], demonstrating that people universally recognise certain basic emotions irrespective of cultural differences. The archetypal facial expressions include anger, contempt, fear, pleasure, sorrow, and surprise. Contempt was then included as one of the fundamental emotions [5]. Recent research in neuroscience and psychology contends that the paradigm of six main emotions is culture-specific rather than universal [6]. Despite the limitations of the affect model grounded in basic emotions in capturing the intricacy and nuance of everyday affective expressions, and although alternative emotion description frameworks,

such as the Facial Action Coding System (FACS) and the continuous model utilising affect dimensions, are regarded as encompassing a broader spectrum of emotions, the categorical model that delineates emotions through discrete basic emotions remains the predominant approach for facial expression recognition (FER), owing to its foundational research and the straightforward, intuitive characterisation of facial expressions. This survey will focus only on FER within the framework of the category _____ model.

FER systems may be classified into two primary kinds based on feature representations: static picture FER and dynamic sequence FER. Static-based approaches [12], [13], [14] encode feature representation only using spatial information from a single picture, whereas dynamic-based methods [15], [16], [17] take into account the temporal relationships among consecutive frames in the input facial expression sequence. In addition to these two vision-based approaches, additional modalities, including audio and physiological channels, have been used in multimodal systems [18] to enhance expression recognition. The most conventional approaches have used handmade features or shallow learning techniques, such as local binary patterns (LBP), LBP on three orthogonal planes (LBP-TOP), non-negative matrix factorisation (NMF), and sparse learning, for facial expression recognition (FER). Since 2013, emotion recognition competitions like FER2013 and Emotion Recognition in the Wild (EmotiW) have amassed adequate training data from challenging real-world contexts, thereby facilitating the shift of facial emotion recognition from controlled laboratory environments to real-world applications. Meanwhile, the significant enhancement of chip processing capabilities (e.g., GPU units) and the optimisation of network architecture have prompted research across diverse disciplines to adopt deep learning techniques, which have attained state-of-the-art recognition accuracy and surpassed prior outcomes substantially (e.g., [25], [26], [27], [28]). Similarly, with the availability of more effective training data for facial expressions, deep learning approaches have been increasingly used to address the complex challenges of emotion identification in real-world scenarios. Figure 1 depicts the progression of FER concerning methods and datasets. Comprehensive surveys on automated expression analysis have been published in recent years [7], [8], [29], [30]. These surveys have produced a standardised set of mathematical pipelines for facial emotion recognition (FER). Nevertheless, their emphasis is on conventional techniques, whereas deep learning has seldom been examined. A new assessment on facial expression recognition (FER) using deep learning is presented in [31], offering a concise overview devoid of introductory information about FER datasets and technical specifics of deep FER. Consequently, this work conducts a thorough investigation of deep learning for facial expression recognition tasks using both static photos and video sequences. Our objective is to provide a newbie to this field with an overview of the methodical framework and essential skills for depth. Despite the robust feature learning capabilities of deep learning, challenges

persist when used to facial emotion recognition (FER). Initially, deep neural networks need a substantial volume of training data to prevent overfitting. Nonetheless, the current facial expression datasets are inadequate for training the renowned deep architecture neural networks that have shown the most promising outcomes in object identification tasks. Moreover, significant inter-subject variability arises from several personal characteristics, including age, gender, ethnic origin, and degree of expressiveness [32]. Alongside subject identification bias, differences in position, lighting, and occlusions often occur in unconstrained facial expression contexts. These parameters are nonlinearly interconnected with face expressions, hence enhancing the need for deep networks to manage significant intra-class variability and to acquire good expression-specific representations.

EXISTING SYSTEM

In the absence of personnel in unmanned eating establishments, it is difficult for management to assess client experiences regarding the idea and the cuisine. Current rating systems, like Google and TripAdvisor, inadequately address this issue, since they include just a fraction of user perspectives. These rating methods are used only by a segment of consumers who independently evaluate the restaurant on external rating sites. This pertains mostly to clients who see their visit as either very favourable or highly unpleasant.

PROPOSED SYSTEM

To address the aforementioned issue, it is imperative that all consumers be incentivised to provide a rating. This article presents a methodology for a restaurant evaluation system that solicits feedback from each client post-visit to maximise the volume of reviews. This method is applicable to unmanned restaurants; the evaluation mechanism relies on face expression recognition via trained convolutional neural network, or CNN, models. It enables the client to evaluate the cuisine by taking a photograph of their facial expression that conveys the associated emotions. In contrast to a text-based grading system, there is much less data available and no specific experience reports gathered. This straightforward, rapid, and engaging rating method aims to provide a broader spectrum of consumer perspectives about their experiences with the dining establishment concept.

SYSTEM ARCHITECTURE



Fig. System Architecture

IMPLEMENTATION

Face detection or localisation is a crucial stage in picture classification, since just the primary facial features, such as the nose, eyes, and mouth, are required for classification. Face identification techniques may be categorised as feature-based, knowledge-based, template-based, and appearance-based approaches. Our suggested method employs the Viola-Jones object identification algorithm for facial localisation, which falls under feature-based classification. The Viola-Jones object identification technique employs Haar feature-based cascade classifiers. The Haar Cascade facial classifier is a crucial component of face detection. The existence of features in any input picture is ascertained by the Haar features.

Facial Expression Recognition classification: Upon acquiring the deep characteristics, the concluding phase of Facial Expression Recognition (FER) is to categorise the presented face into one of the fundamental emotion classifications. In contrast to conventional approaches, where feature extraction and classification are separate processes, deep networks may execute facial expression recognition in an integrated manner. A loss layer is included at the network's conclusion to modulate the back-propagation error, enabling the network to directly output the prediction probability for each sample. In CNN, the softmax loss function is mostly used to minimise the cross-entropy among the predicted class probability and the actual distribution.

Convolutional neural network (CNN): CNN has been widely used in several computer vision applications, including facial emotion recognition (FER). In the early 21st century, numerous studies in the FER literature demonstrated that convolutional neural networks (CNNs) exhibit resilience to alterations in face location and scale variations, outperforming multilayer perceptrons (MLPs) in scenarios involving previously unencountered facial pose variations. The CNN was utilised to tackle issues of subject independence, in addition to translation, rotation, or scale invariance in facial expression recognition.

RESULTS

To execute this project, install MySQL and thereafter build a database by copying the contents of the 'DB.txt' file and pasting it into MySQL. Install Python, then install the Django web framework and deploy the code on Django. Initiate the server post-deployment and execute the code via the browser.



Click the 'User' option on the top page to access the subsequent screen, where users may submit photos and provide reviews.



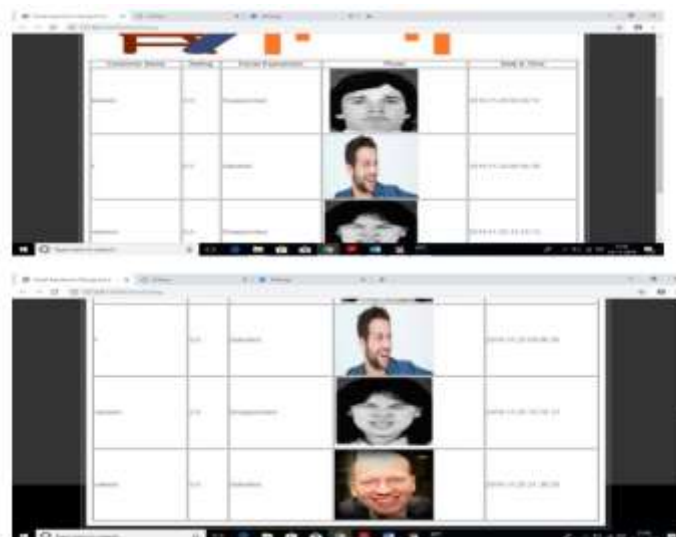
In the aforementioned page, I completed the form, uploaded a cheerful picture, clicked the 'Open' button, and then clicked the 'Submit' button to transmit the data to the web server. Upon processing the aforementioned data, the following findings will be obtained.



The output message seen above indicates the provided rating, and the facial expression recovered from the picture is one of satisfaction. Proceed to the 'Administrator' link and log in as the administrator using the username 'admin' and the password 'admin'. Refer to the screen below.



In the aforementioned panel, the administrator may choose the 'View Users Rating' link to get all customer comments. See below screen.



The administrator may see photographs and their corresponding face expressions from the aforementioned panels.

CONCLUSION

Data bias and incorrect annotations often occur across various facial expression datasets owing to differing collection settings and the subjectivity inherent in annotation. Researchers often assess their algorithms using a designated dataset and may get acceptable performance. Early cross-database experiments have revealed that discrepancies among databases arise from varying collection environments or construction indicators [12]; consequently, algorithms assessed through intra-database protocols exhibit limited generalisability on unseen test data, resulting in significantly diminished performance in cross-dataset contexts. Deep domain adaptation and knowledge distillation provide as options to mitigate this bias [226], [251]. Moreover, due to the inconsistent expressions annotations, the performance of FER cannot continue to improve by simply amalgamating various datasets for training purposes [167]. A prevalent issue in facial expression analysis is class imbalance, stemming from the practicality of data collection: eliciting / annotating a grin is straightforward.

REFERENCES

- [1] T. Cherry Pears Sk.Mahaboob Basha, Y. Akhil , K. Murari, DESIGNING A RECOMMENDED SYSTEM FOR PRODUCT MANUFACTURER. The International journal of analytical and experimental modal analysis Volume XV, Issue I, January/2023 ISSN NO: 0886-9367
- [2] Y.-I. Tian, T. Kanade, and J. F. Cohn, "Recognizing action units for facial expression analysis," IEEE Transactions on pattern analysis and machine intelligence, vol. 23, no. 2, pp. 97–115, 2001.
- [3] P. Ekman and W. V. Friesen, "Constants across cultures in the face and emotion." Journal of personality and social psychology, vol. 17, no. 2, pp. 124–129, 1971.
- [4] P. Ekman, "Strong evidence for universals in facial expressions: a reply to russell's mistaken critique," Psychological bulletin, vol. 115, no. 2, pp. 268–287, 1994.
- [5] D. Matsumoto, "More evidence for the universality of acontempt expression," Motivation and Emotion, vol. 16, no. 4, pp. 363–368, 1992.
- [6] R. E. Jack, O. G.Garrod, H. Yu, R. Caldara, and P. G. Schyns, "Facial expressions of emotion are not culturally universal," Proceedings of the National Academy of Sciences, vol. 109, no. 19, pp. 7241–7244, 2012.
- [7] Ministerio de Salud y Protecci'ón Social. Analisis de situacion de salud visual en Colombia, 2016.
- [8] Ravindra Changala, "Secured Activity Based Authentication System" in " in Journal of innovations in computer science and engineering (JICSE), Volume 6, Issue 1,Pages 1-4, September 2016.ISSN: 2455-3506.
- [9] S. S. Kanse and D. M. Yadav. Retinal fundus image for glaucoma detection: A review and study. Journal of Intelligent Systems, 28(1):43– 56, 2017.
- [10] S. Nawaldgi. Review of automated glaucoma detection techniques. In 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), pages 1435–1438, 2016.
- [11] Ravindra Changala, "Online Attendance using PCA Based Image Face Recognition" to publish in "International Journal for Research in Applied Science and Engineering Technology (IJRASET)" with Impact Factor 1.241, ISSN: 2321-9653,Volume 2, Issue XII, December 2014.

- [12] C. Anusorn, W. Kongprawechnon, T. Kondo, S. Sintuwong, and K. Tungpimolrut. Image processing techniques for glaucoma detection using the cup-to-disc ratio. *Science and Technology Asia*, 18(1):22–34, 2013.
- [13] C. Dhumane and S.B. Patil. Automated glaucoma detection using cup to disc ratio. *International Journal of Innovative Research in Science, Engineering and Technology*, 4(7):5209–5216, 2015.
- [14] Ravindra Changala, Framework for Virtualized Network Functions (VNFs) in Cloud of Things Based on Network Traffic Services, *International Journal on Recent and Innovation Trends in Computing and Communication*, ISSN: 2321-8169 Volume 11, Issue 11s, August 2023.
- [15] Ravindra Changala, “Optimization of Irrigation and Herbicides Using Artificial Intelligence in Agriculture”, *International Journal of Intelligent Systems and Applications in Engineering*, Volume 11, Issue 3), July 2023.