Journal of Robotics and Control (JRC)
Volume 5, Issue 1, 2024
ISSN: 2715-5072, DOI: 10.18196/jrc.v5i1.20895

Using Learning Focal Point Algorithm to Classify Emotional Intelligence

Abdelhak Sakhi [1*], Salah-Eddine Mansour [2], Abderrahim Sekkaki [3]
[1, 2, 3] Electrical and Industrial Engineering Information Processing IT and logistics (GEIIL), Faculty of Sciences Ain Chock, Hassan 2 University, Casablanca, Morocco
Email: [1] sakhi442@gmail.com, [2] 19mansour94@gmail.com, [3] sekkabd@gmail.com
*Corresponding Author

***Abstract*—Recognizing the fundamental role of learners' emotions in the educational process, this study aims to enhance educational experiences by incorporating emotional intelligence (EI) into teacher robots through artificial intelligence and image processing technologies. The primary hurdle addressed is the inadequacy of conventional methods, particularly convolutional neural networks (CNNs) with pooling layers, in imbuing robots with emotional intelligence. To surmount this challenge, the research proposes an innovative solution—introducing a novel learning focal point (LFP) layer to replace pooling layers, resulting in significant enhancements in accuracy and other vital parameters. The distinctive contribution of this research lies in the creation and application of the LFP algorithm, providing a novel approach to emotion classification for teacher robots. The results showcase the LFP algorithm's superior performance compared to traditional CNN approaches. In conclusion, the study highlights the transformative impact of the LFP algorithm on the accuracy of classification models and, consequently, on emotionally intelligent teacher robots. This research contributes valuable insights to the convergence of artificial intelligence and education, with implications for future advancements in the field.**

***Keywords*—Perceptron; LFP Algorithm; CNN; Neural Network; Emotional Intelligence.**

I. INTRODUCTION

In the rapidly evolving landscape of technological advancements, the fusion of artificial intelligence and robotics is ushering in transformative changes across various facets of our lives. Notably, the realm of education emerges as a particularly promising domain in this era of innovation. This research stands at the forefront of these developments, actively contributing to the creation of a state-of-the-art teacher robot that seamlessly integrates [1], [2]. A primary and innovative focus of this endeavor lies in the infusion of emotional intelligence (EI) into robot teachers, achieved through the sophisticated analysis of facial expressions using advanced artificial intelligence techniques [3], [4], [5].

Acknowledging the pivotal role of emotional intelligence in the realm of education unveils a profound connection between a teacher's proficiency in conveying information and a student's ability to not just comprehend but actively engage with the material. The dynamics of the learning process extend beyond the mere transmission of facts; they are intricately interwoven with the emotional landscape within the classroom. This research undertakes the formidable challenge of seamlessly integrating emotional intelligence into the fabric of robot teachers, with a deliberate emphasis on the significance of understanding and appropriately responding to students' emotions. By doing so, it seeks to enhance the effectiveness of the teaching and learning experience, recognizing that the emotional context within the educational setting plays a crucial role in shaping the overall success of the educational process [6], [7], [8], [9].

In the same scientific context, our inquiry extended to the methodologies employed in artificial intelligence for the classification of emotions based on facial expressions. Our findings reveal a predominant reliance on deep learning techniques involving the training of neural networks, signifying a concentration of innovations within the domain of deep learning architecture [10], [11]. Specifically, the convolutional neural network (CNN) emerges as a widely adopted architectural structure in facial recognition. This prevalence is evident in the utilization of CNN-based solutions and frameworks like DeepFace, FaceNet, and LightCNN, all of which leverage CNNs, subsequently relying on pooling layers. The incorporation of pooling layers is integral to managing computational resources, curtailing the number of parameters, and concentrating on pivotal features within the data [12], [13], [14].

CNNs have exhibited remarkable efficacy in diverse computer vision tasks, attributed to their intrinsic capability to autonomously acquire hierarchical representations of features from input data. Named after the convolutional layers that apply filters or kernels to input data, CNNs slide these filters over the input, capturing local patterns and features. The outcome is a feature map that accentuates pertinent structures in the input. Within the CNN framework, pooling layers assume a critical role by reducing the spatial dimensionality of input data, effectively controlling the network's computational complexity and parameter count. Pooling serves as a down-sampling process, implemented post-convolutional layers, preserving essential information while diminishing spatial resolution [15], [16], [17], [18]. The two common types of pooling layers include max pooling and average pooling. Max pooling, a prevalent technique, involves selecting the maximum value from a group of neighboring pixels in the input, aiming to retain the most crucial features and diminish spatial dimensions. Conversely, average pooling computes the average value from a group of neighboring pixels, contributing to the nuanced processing of spatial information.

Our scholarly innovation is evident in the substitution of conventional pooling layers with the Learning Focal Point

(LFP) layer—a pioneering methodology that notably amplifies the robot's proficiency in categorizing student emotions. The ensuing sections intricately expound upon the elucidation of the LFP algorithm, the disclosure of results, and the evaluation of performance, collectively furnishing a thorough comprehension of the introduced methodology. Furthermore, the article delves into a discourse on the design intricacies and mathematical theories that form the foundational framework of the LFP algorithm. This comprehensive discussion not only underscores the practical application of our research but also underscores the theoretical underpinnings that contribute to the efficacy and innovation of the proposed LFP layer in the realm of emotional intelligence for teacher robots [19], [20], [21].

In this article, in section 2, we will explain the LFP algorithm and how we can use it for emotion classification. In section 3, we will discuss the results and performance of using the LFP algorithm in this case. Followed by the conclusion. we will present the design and mathematical theories on which the LFP algorithm is based.

II. RESEARCH METHOD

A. Emotion Classification System

Our emotion classification system, illustrated in Fig. 1, comprises three essential modules that collectively contribute to the intricate process of deciphering emotions from facial expressions.

In the initial module of our emotion classification system, the robust capabilities of the OpenCV library are harnessed to meticulously identify and track the student's face. Through adept video or image analysis, this module ensures precise face detection, laying a crucial foundation for subsequent emotion analysis. The reliance on OpenCV equips the system with sophisticated tools for navigating diverse environmental conditions and capturing nuanced facial expressions, establishing a robust basis for understanding and interpreting the student's emotional states. The precision achieved in this initial step enhances the overall accuracy and effectiveness of the subsequent emotion classification process [22], [23], [24], [25].

In the second module of our emotion classification system, we capitalize on the cutting-edge Learning Focal Point (LFP) algorithm, introducing an innovative approach to facial feature extraction. This algorithm assumes a pivotal role in identifying and precisely determining the coordinates of essential facial features, thereby extracting key regions of the face with unparalleled accuracy. The Learning Focal Point (LFP) algorithm stands out for its capability to capture nuanced details, facilitating a sophisticated interpretation of emotions. By honing in on these essential facial features, the algorithm contributes to a comprehensive understanding of the subtle nuances in the student's expressions, enriching the subsequent stages of emotion analysis and enhancing the system's ability to discern and categorize a diverse range of emotional states with precision [26], [27], [28].

In the third module of our emotion classification system, a pivotal role is assumed as it undertakes the intricate task of computing the weights of the neural network, which is imperative for the subsequent nuanced classification of facial expressions. This critical step involves complex calculations that strategically leverage the information extracted by the Learning Focal Point (LFP) algorithm in the preceding module. By meticulously processing the coordinates and nuanced details identified by the LFP algorithm, the system is equipped to discern and interpret a spectrum of emotional states based on the intricacies of the identified facial features. This computational approach ensures that the neural network is finely tuned to capture the subtle variations in expressions, allowing for a sophisticated and accurate classification of the diverse range of emotional nuances exhibited by the students.

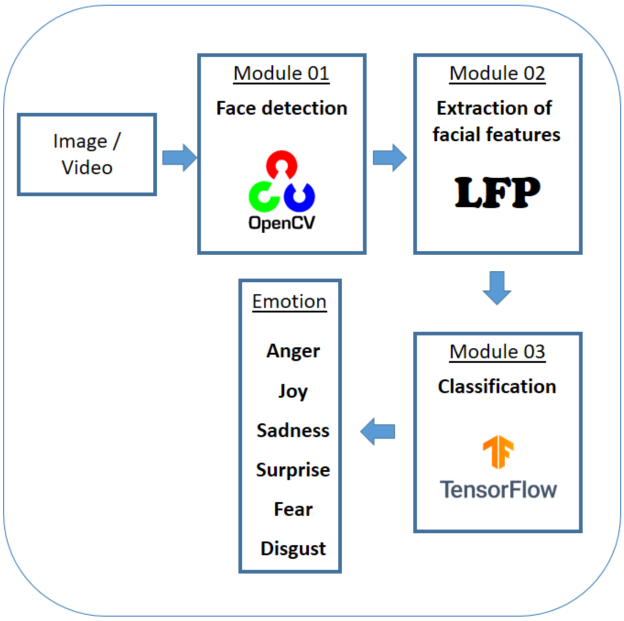

Fig. 1. Emotion classification system modules

B. Dataset

The dataset employed in this study is sourced from the "Representation Learning Challenges: Facial Expression Recognition (FER) Challenge" hosted on Kaggle, where its primary objective is to tackle the classification of facial expressions into distinct emotion categories. Typically, this dataset comprises images, each labeled with one of several emotion classes, including happiness, sadness, anger, surprise, fear, disgust, and neutral. For the purpose of training our neural network, we utilized this dataset to impart a diverse range of facial expressions and emotions. It is noteworthy that the specific database utilized in the Kaggle Facial Expression Recognition Challenge is likely the Facial Expression Recognition 2013 (FER2013) dataset. This dataset is characterized by 48x48-pixel grayscale images depicting faces, with each image associated with one of seven emotions. With an extensive collection of around 35,000 images, the dataset offers a rich and varied set of facial expressions, facilitating the robust training of our neural network across seven different emotional categories [29], [30], [31], [32].

This dataset serves as a crucial testing ground for evaluating the efficacy of our emotional intelligence detection system. By subjecting our system to this dataset, we aim to conduct a comprehensive examination of its performance in the context of facial expression recognition and emotion classification. The dataset's diverse array of images, each labeled with specific emotion categories, enables us to assess the system's ability to accurately detect and classify a spectrum of emotions, including happiness, sadness, anger, surprise, fear, disgust, and neutral expressions. Executing our system on this dataset provides an empirical measure of its proficiency, allowing us to scrutinize its accuracy, sensitivity, and overall performance in handling real-world facial expressions and emotional nuances. This evaluation on a well-established benchmark like the Kaggle Facial Expression Recognition Challenge dataset enhances the reliability and applicability of our system in addressing broader scenarios related to emotional intelligence detection [33], [34], [35], [36].

C. *OpenCV*

Open Source Computer Vision (OpenCV) Library stands as a versatile and extensive toolbox, encompassing a myriad of functionalities tailored for diverse image processing tasks. From fundamental operations like image filtering, transformation, enhancement, to more intricate geometric manipulations such as resizing, cropping, and rotation, OpenCV provides a comprehensive suite of tools that caters to the entire spectrum of image processing needs. Its capabilities extend beyond traditional image processing, incorporating features for computer vision, machine learning, and advanced image analysis. With its core implementation in C++, OpenCV also offers interfaces for Python, Java, and various other programming languages, ensuring accessibility and ease of integration across different platforms [37], [38], [39], [40].

In addition to basic image processing functions, OpenCV boasts an array of advanced capabilities, including morphological operations, color space transformations, and an extensive set of computer vision algorithms. These algorithms cover a broad range of applications, including object detection, feature extraction, image stitching, and camera calibration [41], [42], [43]. Moreover, OpenCV seamlessly integrates with popular machine learning frameworks, providing support for essential tasks like classification, clustering, and regression. Its compatibility with deep learning frameworks such as TensorFlow and PyTorch further extends its utility, enabling users to work with both pre-trained deep learning models and construct their own models. In essence, OpenCV stands as a powerful and adaptable tool for a wide array of image processing and computer vision applications, catering to the needs of diverse users and scenarios [44], [45], [46].

In our specific implementation, we employed the OpenCV library to facilitate the detection and extraction of images depicting children's faces. As depicted in Fig. 2, OpenCV dynamically encapsulates each human face in the image by outlining it with a distinctive red square. This process involves leveraging OpenCV's robust computer vision capabilities, which enable accurate face identification and localization within the images captured by the cameras that will be strategically installed. The utilization of OpenCV ensures a reliable and precise facial detection mechanism, setting the stage for subsequent stages of image analysis and emotion classification within our system [47], [48], [49], [50].

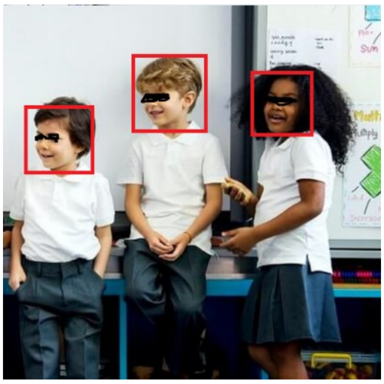

Fig. 2. Students' faces are outlined with red squares using OpenCV

D. *Learning Focal Point (LFP) Algorithm*

Initially, it is essential to introduce the origin and inspiration behind the Learning Focal Point (LFP) algorithm. Drawing inspiration from the brain's learning process, we observed that, before learning to classify objects, it first distinguishes the differences among them. To validate this concept, we conducted an experiment with 100 students, presenting an image featuring drawings of a man and a woman. All students accurately identified the gender of each shape. Subsequently, we inquired about the specific body area they relied on for gender determination. The results, illustrated in Fig. 3, revealed that 43% focused on the head, while 57% considered the chest shape. This experiment demonstrated that students based their answers on discerning distinctive areas in the two bodies, mirroring the functionality of the LFP algorithm. It identifies distinguishing areas in images for subsequent utilization in machine learning [51], [52], [53].

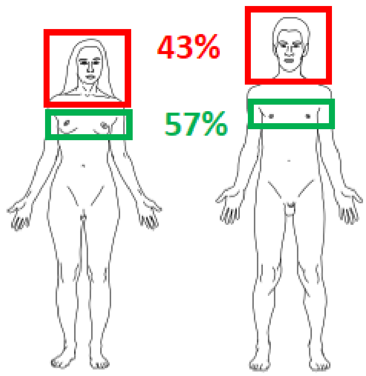

Fig. 3. Points of difference between the female and male body

To gain a comprehensive understanding of the functionality of the Learning Focal Point algorithm, it is essential to delve into the intricacies of the associated flowchart, as depicted in Fig. 4. The algorithm unfolds in a series of well-defined steps, each contributing to the ultimate goal of identifying the key focal points in the input images.

The initial step in this algorithmic process involves the segmentation of each image into distinct parts, denoted as Div[i]. This implies a meticulous partitioning of the image, where Div[i] represents a specific segment or region within the overall image. The subdivision of images into these parts lays the foundation for subsequent analysis and enables the algorithm to focus on localized features, see Fig. 5.

Moving forward, the second step entails the execution of a perceptron for each group of Div[i]. The perceptron, a fundamental building block of neural networks, plays a crucial role in processing the information contained within each segmented region. This step involves the utilization of perceptrons to extract relevant features and patterns from the individual Div[i] segments.

Following the execution of perceptrons, the algorithm proceeds to calculate the accuracy of each group, as exemplified by equation (1). This accuracy computation serves as a metric to evaluate the effectiveness of the algorithm in identifying significant focal points within each segmented part [54], [55], [56]. It provides a quantitative measure of the algorithm's ability to discern relevant features in relation to the specific Div[i] regions.

Subsequently, the algorithm undertakes the critical task of sorting the Div[i] segments in descending order of precision, as denoted by Pr(Div[i]). Precision, in this context, serves as a pivotal criterion for determining the significance of each segment. Sorting the segments based on precision ensures that the algorithm prioritizes those regions with the highest accuracy, emphasizing their importance in the overall analysis.

In the final step of the Learning Focal Point algorithm, the coordinates of the segmented parts with the highest precision are returned. This culmination of the algorithmic process signifies the identification and localization of key focal points within the input images. By prioritizing and extracting the most relevant information, the algorithm effectively distills the complexity of the images into essential components, facilitating a focused and nuanced analysis of the underlying features.

$$Accuracy = \frac{True\ Positive + False\ Positive}{Total} \tag{1}$$

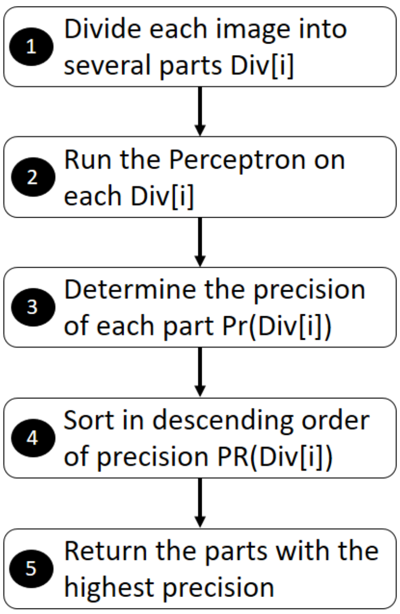

Fig. 4. Flowchart of the LFP algorithm

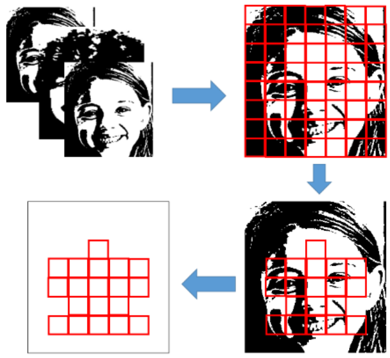

Fig. 5. Execution of perceptron on several square

E. *TensorFlow*

TensorFlow is an open-source machine learning framework developed by the Google Brain team. It's designed to facilitate the development and deployment of machine learning models. TensorFlow has strong support for building and training Convolutional Neural Networks (CNNs). CNNs are a specific type of neural network architecture that is particularly effective for image-related tasks, such as image classification, object detection, and image segmentation. TensorFlow provides a comprehensive ecosystem for developing and deploying machine learning models. It offers a high-level API called Keras that simplifies the process of building and training neural networks, including CNNs. TensorFlow allows users to define, train, and deploy complex models efficiently. Keras is an open-source high-level neural networks API that is now tightly integrated into TensorFlow. With Keras, we can easily build and experiment with various neural network architectures, including CNNs, using a clear and user-friendly syntax [57], [58], [59].

TensorFlow stands out as a paramount choice in neural network training due to its versatile and modular architecture, accommodating the creation of complex models tailored to specific applications [60], [61], [62]. The framework's scalability proves pivotal, seamlessly transitioning from single-device training to distributed environments, leveraging GPUs or TPUs for enhanced efficiency with large datasets. TensorFlow's extensive community support provides a wealth of resources, tutorials, and collaborative knowledge-sharing. The integration of TensorBoard offers a clear visualization tool for monitoring training processes, metrics, and model performance. TensorFlow's compatibility with various platforms ensures ease of deployment, vital for practical implementation across diverse environments. High-level APIs like Keras simplify model design, making the framework accessible for both novices and experts. Optimizations for hardware utilization, including GPU acceleration and TPU integration, contribute to significant speedups in training. The constant updates and improvements driven by ongoing research keep TensorFlow at the forefront of machine learning technology, allowing users to leverage the latest advancements for optimal model performance. In our application, TensorFlow's adaptability, scalability, community support, and visualization tools are instrumental, making it an indispensable asset for achieving optimal results and advancing our specific goals [63], [64], [65], [66].

Thus, the neural network is trained using the squares identified by the Learning Focal Point (LFP) algorithm, illustrated in Fig. 6. These squares act as critical inputs, guiding the network in learning patterns associated with specific features within these regions. This approach aligns with supervised learning principles, enhancing the network's ability to generalize to new data. Integrating the LFP algorithm's findings into the training process strategically optimizes the neural network's learning and performance on the targeted task.

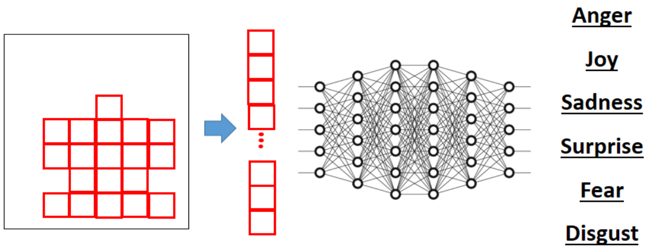

Fig. 6. Training the neural network using the squares found by the LFP algorithm

III. RESULT AND DISCUSSION

Following an exploration of the methodologies employed in this research, our focus now shifts to presenting and analyzing the results obtained through the utilization of the Learning Focal Point (LFP) algorithm. A key aspect of this analysis involves a comparative examination with the outcomes derived from employing the widely utilized MaxPooling technique [67], [68], [69]. This comparative evaluation aims to underscore the significance of the Learning Focal Point algorithm in enhancing the performance of neural networks. Two distinct experiments have been conducted for this purpose. In the first experiment, MaxPooling is applied after the neural network, while in the second experiment, the Learning Focal Point algorithm is integrated with the neural network. To provide a concrete understanding of the comparative assessment, we have computed and analyzed essential metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC, for each experiment. This comprehensive evaluation aims to elucidate the distinctive impact and advantages of the Learning Focal Point algorithm in contrast to the conventional Max-Pooling technique, thereby shedding light on its pivotal role in improving the overall effectiveness of neural network-based applications [70], [71], [72], [73].

Commonly used in machine learning tasks, performance metrics like Accuracy, Precision, Recall, F1-score, and ROC-AUC offer distinct insights into the effectiveness of classification models. Accuracy, a measure of overall correctness, represents the ratio of correctly predicted instances to the total instances in the dataset. Precision, emphasizing positive prediction accuracy, is particularly relevant when minimizing false positives is crucial. Recall, highlighting the avoidance of false negatives, measures the model's ability to identify all relevant instances. The F1-score, a harmonic mean of precision and recall, proves useful in scenarios with uneven class distributions. ROC-AUC, applied in binary classification, assesses the trade-off between sensitivity and specificity, with a higher AUC indicating superior model performance. Collectively, these metrics provide a comprehensive evaluation, covering correctness, positive prediction accuracy, avoidance of false negatives, balanced precision and recall, and the trade-off between sensitivity and specificity in classification models [74], [75], [76], [77].

The evaluation of distinct methodologies was undertaken through the implementation of two experiments, as visually depicted in Fig. 7. In the initial experiment, the integration of the Learning Focal Point (LFP) algorithm with the neural network was employed, aiming to harness the algorithm's capabilities in enhancing feature identification. Conversely, the second experiment focused exclusively on the utilization of max pooling, a conventional technique in neural network architectures. A comprehensive analysis of the outcomes from both experiments is presented in Table I, providing valuable insights into the comparative performance of these methodologies [78], [79], [80], [81], [82].

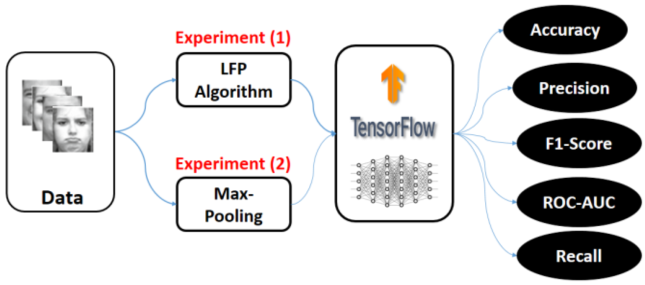

Fig. 7. Training the neural network using the squares found by the LFP algorithm.

TABLE I. RESULTS OF TWO EXPERIMENTS

Algorithm	*CA*	*Precision*	*Recall*	*F1-Score*	*ROC-AUC*
LFP	0.93	0.93	0.93	0.93	0.94
Max-Pooling	0.82	0.82	0.82	0.82	0.83

The results underscore the robust and notable performance of the LFP algorithm, particularly emphasizing its precision in identifying relevant features within the dataset. The comparison between the outcomes of Experiments 1 and 2 reveals a significant observation: the integration of the LFP algorithm contributes to a substantial enhancement in classification accuracy, with improvements of up to 10%. This noteworthy finding underscores the tangible benefits of incorporating the Learning Focal Point algorithm, indicating its potential to significantly elevate the overall effectiveness of the neural network in capturing intricate patterns and enhancing its classification capabilities.

IV. CONCLUSION

In conclusion, our study focuses on integrating the Learning Focal Point (LFP) algorithm into the Automated Tutor project, aiming to enhance emotion classification within educational settings. The practical importance of our findings lies in the significant improvement, up to 10% under specific conditions, in sentiment classification accuracy achieved by replacing traditional pooling layers with the LFP algorithm in the convolutional neural network architecture. This advancement directly contributes to the development of the Automated Tutor, promoting emotional intelligence and enabling more nuanced interactions with students. Looking forward, avenues for future research include exploring advanced machine learning algorithms and considering additional features to refine emotion recognition. While acknowledging the specific conditions for improved accuracy, it is essential to further investigate the generalizability of the LFP algorithm's success in diverse educational contexts. In closing, our work not only advances emotion classification but also encourages collaborative efforts for continued refinement and application in educational technology.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to the National Center for Scientific and Technical Research (CNRST)-Morocco for their generous support and assistance throughout the duration of this research project. Their commitment to advancing scientific knowledge and their dedication to achieving our research goals were instrumental in the success of this work, which is part of the Al-Khwarizmi Program.

REFERENCES

[1] F. Zhou, S. Hu, X. Wan, Z. Lu, and J. Wu, "Diplin: A Disease Risk Prediction Model Based on EfficientNetV2 and Transfer Learning Applied to Nursing Homes," *Electronics*, vol. 12, no. 12, p. 2581, 2023, doi: 10.3390/electronics12122581.

[2] S. Kwon *et al.*, "Empirical Comparison of Supervised Learning Methods for Assessing the Stability of Slopes Adjacent to Military Operation Roads," Forests, vol. 14, no. 6, p. 1237, 2023, doi: 10.3390/f14061237.

[3] D. Masi *et al.*, "Uncovering Predictors of Lipid Goal Attainment in Type 2 Diabetes Outpatients Using Logic Learning Machine: Insights from the AMD Annals and AMD Artificial Intelligence Study Group," *J. Clin. Med.*, vol. 12, no. 12, p. 4095, 2023, doi: 10.3390/jcm12124095.

[4] S. Amaouche *et al.*, "FSCB-IDS: Feature Selection and Minority Class Balancing for Attacks Detection in VANETs," *Appl. Sci.*, vol. 13, no. 13, p. 7488, 2023, doi: 10.3390/app13137488.

[5] R. Amin, Md. S. Reza, Y. Okuyama, Y. Tomioka, and J. Shin, "A Fine-Tuned Hybrid Stacked CNN to Improve Bengali Handwritten Digit Recognition," *Electronics*, vol. 12, no. 15, p. 3337, 2023, doi: 10.3390/electronics12153337.

[6] A. Rahim, Y. Zhong, T. Ahmad, S. Ahmad, P. Pławiak, and M. Hammad, "Enhancing Smart Home Security: Anomaly Detection and Face Recognition in Smart Home IoT Devices Using Logit-Boosted CNN Models," *Sensors*, vol. 23, no. 15, p. 6979, 2023, doi: 10.3390/s23156979.

[7] U. M. Ramirez-Alcocer, E. Tello-Leal, G. Romero, and B. A. Macías-Hernández, "A Deep Learning Approach for Predictive Healthcare Process Monitoring," *Information*, vol. 14, no. 9, p. 508, 2023, doi: 10.3390/info14090508.

[8] M. A. Almaiah *et al.*, "A Novel Approach for Improving the Security of IoT–Medical Data Systems Using an Enhanced Dynamic Bayesian Network," *Electronics*, vol. 12, no. 20, p. 4316, 2023, doi: 10.3390/electronics12204316.

[9] B. Yagin, F. Yagin, C. Colak, F. Inceoglu, S. Kadry, and J. Kim, "Cancer Metastasis Prediction and Genomic Biomarker Identification through Machine Learning and eXplainable Artificial Intelligence in Breast Cancer Research," *Diagnostics*, vol. 13, no. 21, p. 3314, 2023, doi: 10.3390/diagnostics13213314.

[10] H. Lai *et al.*, "Applications of Machine Learning to Diagnosis of Parkinson's Disease," *Brain Sci.*, vol. 13, no. 11, p. 1546, 2023, doi: 10.3390/brainsci13111546.

[11] S. B. Khan, M. Alojail, and M. Al Moteri, "Advancing Disability Management in Information Systems: A Novel Approach through Bidirectional Federated Learning-Based Gradient Optimization," *Mathematics*, vol. 12, no. 1, p. 119, 2023, doi: 10.3390/math12010119.

[12] X. Luo, X. Chen, and Y. Yao, "MVMSGAT: Integrating Multiview, Multi-Scale Graph Convolutional Networks with Biological Prior Knowledge for Predicting Bladder Cancer Response to Neoadjuvant Therapy," *Appl. Sci.*, vol. 14, no. 2, p. 669, 2024, doi: 10.3390/app14020669.

[13] H. T. Gayap and M. A. Akhloufi, "Deep Machine Learning for Medical Diagnosis, Application to Lung Cancer Detection: A Review," *BioMedInformatics*, vol. 4, no. 1, pp. 236–284, 2024, doi: 10.3390/biomedinformatics4010015.

[14] K. M. N. K. Khalif, W. Chaw Seng, A. Gegov, A. S. A. Bakar, and N. A. Shahrul, "Integrated Generative Adversarial Networks and Deep Convolutional Neural Networks for Image Data Classification: A Case Study for COVID-19," *Information*, vol. 15, no. 1, p. 58, 2024, doi: 10.3390/info15010058.

[15] M. Bouazizi, A. L. Mora, K. Feghoul, and T. Ohtsuki, "Activity Detection in Indoor Environments Using Multiple 2D Lidars," *Sensors*, vol. 24, no. 2, p. 626, 2024, doi: 10.3390/s24020626.

[16] L. Cao *et al.*, "U2-Net and ResNet50-Based Automatic Pipeline for Bacterial Colony Counting," *Microorganisms*, vol. 12, no. 1, p. 201, 2024, doi: 10.3390/microorganisms12010201.

[17] K. B. Sachidananda Murthy and S. N. Prasad, "Blockchain-Enabled Detection of Neurological Disorders Using a Deep Learning Approach," in *RAiSE-2023*, p. 187, 2024, doi: 10.3390/engproc2023059187.

[18] L. Lundberg, M. Boldt, A. Borg, and H. Grahn, "Bibliometric Mining of Research Trends in Machine Learning," *AI*, vol. 5, no. 1, pp. 208–236, 2024, doi: 10.3390/ai5010012.

[19] J. Hou, Z. Liu, Z. Yang, and C. Yang, "Hardware Trojan Attacks on the Reconfigurable Interconnections of Field-Programmable Gate Array-Based Convolutional Neural Network Accelerators and a Physically Unclonable Function-Based Countermeasure Detection Technique," *Micromachines*, vol. 15, no. 1, p. 149, 2024, doi: 10.3390/mi15010149.

[20] L. Alhoraibi, D. Alghazzawi, and R. Alhebshi, "Generative Adversarial Network-Based Data Augmentation for Enhancing Wireless Physical Layer Authentication," *Sensors*, vol. 24, no. 2, p. 641, 2024, doi: 10.3390/s24020641.

[21] Y. Wu, L. Huang, W. Feng, and S. Tian, "A Hybrid Deep Learning Algorithm for Tropospheric Zenith Wet Delay Modeling with the Spatiotemporal Variation Considered," *Atmosphere*, vol. 15, no. 1, p. 121, 2024, doi: 10.3390/atmos15010121.

[22] Y. Liu, X. Yan, W. Du, T. Zhang, X. Bai, and R. Nan, "Downscaling Daily Reference Evapotranspiration Using a Super-Resolution Convolutional Transposed Network," *Water*, vol. 16, no. 2, p. 335, 2024, doi: 10.3390/w16020335.

[23] S. Li, N. Jin, A. Dogani, Y. Yang, M. Zhang, and X. Gu, "Enhancing LightGBM for Industrial Fault Warning: An Innovative Hybrid Algorithm," *Processes*, vol. 12, no. 1, p. 221, 2024, doi: 10.3390/pr12010221.

[24] J.-C. Chiu, G.-Y. Lee, C.-Y. Hsieh, and Q.-Y. Lin, "Design and Implementation of Nursing-Secure-Care System with mmWave Radar by YOLO-v4 Computing Methods," *Appl. Syst. Innov.*, vol. 7, no. 1, p. 10, 2024, doi: 10.3390/asi7010010.

[25] C.-H. Liu, S. D. You, and Y.-C. Chiu, "A Reinforcement Learning Approach to Guide Web Crawler to Explore Web Applications for Improving Code Coverage," *Electronics*, vol. 13, no. 2, p. 427, 2024, doi: 10.3390/electronics13020427.

[26] S. K. Poguluri and Y. H. Bae, "Enhancing Wave Energy Conversion Efficiency through Supervised Regression Machine Learning Models," *J. Mar. Sci. Eng.*, vol. 12, no. 1, p. 153, 2024, doi: 10.3390/jmse12010153.

[27] O. Adeniyi, A. S. Sadiq, P. Pillai, M. Aljaidi, and O. Kaiwartya, "Securing Mobile Edge Computing Using Hybrid Deep Learning Method," *Computers*, vol. 13, no. 1, p. 25, 2024, doi: 10.3390/computers13010025.

[28] E. Kalboussi, N. Ndhaief, and N. Rezg, "Last-Mile Optimization Using Neural Networks," *Appl. Sci.*, vol. 14, no. 2, p. 787, 2024, doi: 10.3390/app14020787.

[29] S.-E. Mansour, A. Sakhi, L. Kzaz, O. Tali, and A. Sekkaki, "Focal Point of Learning," in *2021 IEEE 12th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, pp. 0522–0526, 2021, doi: 10.1109/UEMCON53757.2021.9666524.

[30] S.-E. Mansour, A. Sakhi, L. Kzaz, A. Erroutbi, and A. Sekkaki, "Electronic device for acquiring images of sardine cans," In *2022 IEEE World AI IoT Congress (AIIoT)*, pp. 471–475, 2022, doi: 10.1109/AIIoT54504.2022.9817260.

[31] A. Sakhi, S.-E. Mansour, A. Sekkaki, and K. Benzidane, "The Use of the AI to Classify the Emotion Intelligence (EI) Students," In *2022 IEEE 13th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, pp. 0148–0152, 2022, doi: 10.1109/IEMCON56893.2022.9946581.

[32] V. Kemešytė, G. Statkevičiūtė, E. Norkevičienė, and K. Jaškūnė, "Italian Ryegrass as a Forage Crop for the Baltics: Opportunities and Challenges in Light of Climate Change," *Plants*, vol. 12, no. 22, p. 3841, 2023, doi: 10.3390/plants12223841.

[33] A. A. Alothman *et al.*, "Ti3C2-MXene/NiO Nanocomposites-Decorated CsPbI3 Perovskite Active Materials under UV-Light Irradiation for the Enhancement of Crystal-Violet Dye Photodegradation," *Nanomaterials*, vol. 13, no. 23, p. 3026, 2023, doi: 10.3390/nano13233026.

[34] H. Kim, S. Park, and S.-Y. Jeong, "Machine Learning-Based Image Processing for Ice Concentration during Chukchi and Beaufort Sea Trials," *J. Mar. Sci. Eng.*, vol. 11, no. 12, p. 2281, 2023, doi: 10.3390/jmse11122281.

[35] C. Goumy *et al.*, "Feasibility of Optical Genome Mapping from Placental and Umbilical Cord Sampled after Spontaneous or Therapeutic Pregnancy Termination," *Diagnostics*, vol. 13, no. 23, p. 3576, 2023, doi: 10.3390/diagnostics13233576.

[36] Y.-D. Chen and Y.-C. Chang, "AI-DAS: AI-Based Driving Assistance System for Scooters for Traffic Accident Avoidance," In *2023 IEEE 5th Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability*, p. 58, 2023, doi: 10.3390/engproc2023055058.

[37] B. Bąk, J. Wilk, P. Artiemjew, M. Siuda, and J. Wilde, "The Identification of Bee Comb Cell Contents Using Semiconductor Gas Sensors," *Sensors*, vol. 23, no. 24, p. 9811, 2023, doi: 10.3390/s23249811.

[38] A. Boixader, C. Labella, M. Catalan, and J. Paradells, "A High-Accuracy, Scalable and Affordable Indoor Positioning System Using Visible Light Positioning for Automated Guided Vehicles," *Electronics*, vol. 13, no. 1, p. 82, 2023, doi: 10.3390/electronics13010082.

[39] S. B. Rosende, D. S. J. Gavilán, J. Fernández-Andrés, and J. Sánchez-Soriano, "An Urban Traffic Dataset Composed of Visible Images and Their Semantic Segmentation Generated by the CARLA Simulator," *Data*, vol. 9, no. 1, p. 4, 2023, doi: 10.3390/data9010004.

[40] J. Cai, M. Wang, and Y. Wu, "Research on Pedestrian Crossing Decision Models and Predictions Based on Machine Learning," *Sensors*, vol. 24, no. 1, p. 258, 2024, doi: 10.3390/s24010258.

[41] R. Bridgelall, "Alignment of Unsupervised Machine Learning with Human Understanding: A Case Study of Connected Vehicle Patents," *Appl. Sci.*, vol. 14, no. 2, p. 474, 2024, doi: 10.3390/app14020474.

[42] G. G. Md. N. Ali, M. N. Sadat, M. S. Miah, S. A. Sharief, and Y. Wang, "A Comprehensive Study and Analysis of the Third Generation Partnership Project's 5G New Radio for Vehicle-to-Everything Communication," *Future Internet*, vol. 16, no. 1, p. 21, 2024, doi: 10.3390/fi16010021.

[43] S. Y. Alaba, A. C. Gurbuz, and J. E. Ball, "Emerging Trends in Autonomous Vehicle Perception: Multimodal Fusion for 3D Object Detection," *World Electr. Veh. J.*, vol. 15, no. 1, p. 20, 2024, doi: 10.3390/wevj15010020.

[44] F. Pedra, M. L. Inácio, P. Fareleira, P. Oliveira, P. Pereira, and C. Carranca, "Long-Term Effects of Plastic Mulch in a Sandy Loam Soil Used to Cultivate Blueberry in Southern Portugal," *Pollutants*, vol. 4, no. 1, pp. 16–25, 2024, doi: 10.3390/pollutants4010002.

[45] S. Kim, B. S. An, and E. C. Lee, "Comparative Analysis of AI-Based Facial Identification and Expression Recognition Using Upper and Lower Facial Regions," *Appl. Sci.*, vol. 13, no. 10, p. 6070, 2023, doi: 10.3390/app13106070.

[46] S. Gwak and K. Park, "Designing Effective Visual Feedback for Facial Rehabilitation Exercises: Investigating the Role of Shape, Transparency, and Age on User Experience," *Healthcare*, vol. 11, no. 13, p. 1835, 2023, doi: 10.3390/healthcare11131835.

[47] M. Ma and H. Pang, "SP-YOLOv8s: An Improved YOLOv8s Model for Remote Sensing Image Tiny Object Detection," *Appl. Sci.*, vol. 13, no. 14, p. 8161, 2023, doi: 10.3390/app13148161.

[48] O. Adel, K. M. Fathalla, and A. Abo ElFarag, "MM-EMOR: Multi-Modal Emotion Recognition of Social Media Using Concatenated Deep Learning Networks," *Big Data Cogn. Comput.*, vol. 7, no. 4, p. 164, 2023, doi: 10.3390/bdcc7040164.

[49] M. Alonazi, H. J. Alshahrani, F. A. Alotaibi, M. Maray, M. Alghamdi, and A. Sayed, "Automated Facial Emotion Recognition Using the Pelican Optimization Algorithm with a Deep Convolutional Neural Network," *Electronics*, vol. 12, no. 22, p. 4608, 2023, doi: 10.3390/electronics12224608.

[50] N. Anđelić, S. Baressi Šegota, and Z. Car, "Improvement of Malicious Software Detection Accuracy through Genetic Programming Symbolic Classifier with Application of Dataset Oversampling Techniques," *Computers*, vol. 12, no. 12, p. 242, 2023, doi: 10.3390/computers12120242.

[51] R. Venkatesan, S. Shirly, M. Selvarathi, and T. J. Jebaseeli, "Human Emotion Detection Using DeepFace and Artificial Intelligence," In *RAiSE-2023*, p. 37, 2023, doi: 10.3390/engproc2023059037.

[52] H. Xu, J. Kong, X. Kong, J. Li, and J. Wang, "MCF-Net: Fusion Network of Facial and Scene Features for Expression Recognition in the Wild," *Appl. Sci.*, vol. 12, no. 20, p. 10251, 2022, doi: 10.3390/app122010251.

[53] Y. Gao, Y. Cai, X. Bi, B. Li, S. Li, and W. Zheng, "Cross-Domain Facial Expression Recognition through Reliable Global–Local Representation Learning and Dynamic Label Weighting," *Electronics*, vol. 12, no. 21, p. 4553, 2023, doi: 10.3390/electronics12214553.

[54] S. Eddine Mansour, A. Sakhi, L. Kzaz, O. Tali, and A. Sekkaki, "Design, security and implementation of learning focal point algorithm in a docker container," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 33, no. 1, p. 416, 2024, doi: 10.11591/ijeecs.v33.i1.pp416-424.

[55] J. Chang and M. Wang, "Design of Hardware IP for 128-Bit Low-Latency Arcsinh and Arccosh Functions," *Electronics*, vol. 12, no. 22, p. 4658, 2023, doi: 10.3390/electronics12224658.

[56] S. Sun, M. E. Alkahtani, S. Gaisford, A. W. Basit, M. Elbadawi, and M. Orlu, "Virtually Possible: Enhancing Quality Control of 3D-Printed Medicines with Machine Vision Trained on Photorealistic Images," *Pharmaceutics*, vol. 15, no. 11, p. 2630, 2023, doi: 10.3390/pharmaceutics15112630.

[57] S. V. H. Pham and K. V. T. Nguyen, "Productivity Assessment of the Yolo V5 Model in Detecting Road Surface Damages," *Appl. Sci.*, vol. 13, no. 22, p. 12445, 2023, doi: 10.3390/app132212445.

[58] A. Ali, N. Zhang, and R. M. Santos, "Mineral Characterization Using Scanning Electron Microscopy (SEM): A Review of the Fundamentals, Advancements, and Research Directions," *Appl. Sci.*, vol. 13, no. 23, p. 12600, 2023, doi: 10.3390/app132312600.

[59] A. M. Girardi, E. A. Cardell, and S. P. Bird, "Artificial Intelligence in the Interpretation of Videofluoroscopic Swallow Studies: Implications and Advances for Speech–Language Pathologists," B*ig Data Cogn. Comput.*, vol. 7, no. 4, p. 178, 2023, doi: 10.3390/bdcc7040178.

[60] D. Giansanti, "An Umbrella Review of the Fusion of fMRI and AI in Autism," *Diagnostics*, vol. 13, no. 23, p. 3552, 2023, doi: 10.3390/diagnostics13233552.

[61] I. Razveeva *et al.*, "Analysis of Geometric Characteristics of Cracks and Delamination in Aerated Concrete Products Using Convolutional Neural Networks," *Buildings*, vol. 13, no. 12, p. 3014, 2023, doi: 10.3390/buildings13123014.

[62] X. Gao, K. Zhao, L. Han, and J. Luo, "BézierCE: Low-Light Image Enhancement via Zero-Reference Bézier Curve Estimation," *Sensors*, vol. 23, no. 23, p. 9593, 2023, doi: 10.3390/s23239593.

[63] G. Dipalma *et al.*, "Artificial Intelligence and Its Clinical Applications in Orthodontics: A Systematic Review," *Diagnostics*, vol. 13, no. 24, p. 3677, 2023, doi: 10.3390/diagnostics13243677.

[64] H. Mohammadi, K. Thirunarayan, and L. Chen, "CVII: Enhancing Interpretability in Intelligent Sensor Systems via Computer Vision Interpretability Index," *Sensors*, vol. 23, no. 24, p. 9893, 2023, doi: 10.3390/s23249893.

[65] H. Sheng and M. S. Nisar, "Simulating an Integrated Photonic Image Classifier for Diffractive Neural Networks," *Micromachines*, vol. 15, no. 1, p. 50, 2023, doi: 10.3390/mi15010050.

[66] K. Khalaf *et al.*, “From Staining Techniques to Artificial Intelligence: A Review of Colorectal Polyps Characterization,” *Medicina (Mex.)*, vol. 60, no. 1, p. 89, 2024, doi: 10.3390/medicina60010089.

[67] S. Jalalifar *et al.*, “Enhancing Water Safety: Exploring Recent Technological Approaches for Drowning Detection,” *Sensors*, vol. 24, no. 2, p. 331, 2024, doi: 10.3390/s24020331.

[68] Y. Zhang, H. Feng, Y. Zhao, and S. Zhang, “Exploring the Application of the Artificial-Intelligence-Integrated Platform 3D Slicer in Medical Imaging Education,” *Diagnostics*, vol. 14, no. 2, p. 146, 2024, doi: 10.3390/diagnostics14020146.

[69] O. Capetillo-Contreras, F. D. Pérez-Reynoso, M. A. Zamora-Antuñano, J. M. Álvarez-Alvarado, and J. Rodríguez-Reséndiz, “Artificial Intelligence-Based Aquaculture System for Optimizing the Quality of Water: A Systematic Analysis,” *J. Mar. Sci. Eng.*, vol. 12, no. 1, p. 161, 2024, doi: 10.3390/jmse12010161.

[70] H.-J. Yoo *et al.*, “Prediction of Beach Sand Particle Size Based on Artificial Intelligence Technology Using Low-Altitude Drone Images,” *J. Mar. Sci. Eng.*, vol. 12, no. 1, p. 172, 2024, doi: 10.3390/jmse12010172.

[71] Y. Sui, L. Zhang, Z. Sun, W. Yi, and M. Wang, “Research on Coal and Rock Recognition in Coal Mining Based on Artificial Neural Network Models,” *Appl. Sci.*, vol. 14, no. 2, p. 864, 2024, doi: 10.3390/app14020864.

[72] H. S. Munawar, A. W. A. Hammad, S. T. Waller, M. J. Thaheem, and A. Shrestha, “An Integrated Approach for Post-Disaster Flood Management Via the Use of Cutting-Edge Technologies and UAVs: A Review,” *Sustainability*, vol. 13, no. 14, p. 7925, 2021, doi: 10.3390/su13147925.

[73] B. Xu *et al.*, “Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle,” *Agriculture*, vol. 11, no. 11, p. 1062, 2021, doi: 10.3390/agriculture11111062.

[74] R. R. Devaram, G. Beraldo, R. De Benedictis, M. Mongiovì, and A. Cesta, “LEMON: A Lightweight Facial Emotion Recognition System for Assistive Robotics Based on Dilated Residual Convolutional Neural Networks,” *Sensors*, vol. 22, no. 9, p. 3366, 2022, doi: 10.3390/s22093366.

[75] A. Bhardwaj, S. Kishore, and D. K. Pandey, “Artificial Intelligence in Biological Sciences,” *Life*, vol. 12, no. 9, p. 1430, 2022, doi: 10.3390/life12091430.

[76] J. Jiang, X. Ma, D. Ouyang, and R. O. Williams, “Emerging Artificial Intelligence (AI) Technologies Used in the Development of Solid Dosage Forms,” *Pharmaceutics*, vol. 14, no. 11, p. 2257, 2022, doi: 10.3390/pharmaceutics14112257.

[77] M. F. Almufareh, S. Tehsin, M. Humayun, and S. Kausar, “A Transfer Learning Approach for Clinical Detection Support of Monkeypox Skin Lesions,” *Diagnostics*, vol. 13, no. 8, p. 1503, 2023, doi: 10.3390/diagnostics13081503.

[78] X. Peng, Y. Wang, X. Zhang, H. Yang, X. Tang, and S. Bai, “A 6G-Enabled Lightweight Framework for Person Re-Identification on Distributed Edges,” *Electronics*, vol. 12, no. 10, p. 2266, 2023, doi: 10.3390/electronics12102266.

[79] G. Monteiro *et al.*, “A Comprehensive Framework for Industrial Sticker Information Recognition Using Advanced OCR and Object Detection Techniques,” *Appl. Sci.*, vol. 13, no. 12, p. 7320, 2023, doi: 10.3390/app13127320.

[80] A. Zargham *et al.*, “Revolutionizing Small-Scale Retail: Introducing an Intelligent IoT-based Scale for Efficient Fruits and Vegetables Shops,” *Appl. Sci.*, vol. 13, no. 14, p. 8092, 2023, doi: 10.3390/app13148092.

[81] C. Frascarelli et al., “Revolutionizing Cancer Research: The Impact of Artificial Intelligence in Digital Biobanking,” *J. Pers. Med.*, vol. 13, no. 9, p. 1390, 2023, doi: 10.3390/jpm13091390.

[82] T.-J. Tung, M. Al-Hussein, and P. Martinez, “Vision-Based Guiding System for Autonomous Robotic Corner Cleaning of Window Frames,” *Buildings*, vol. 13, no. 12, p. 2990, 2023, doi: 10.3390/buildings13122990.