International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 13, Issue 4 [April. 2024] PP: 169-172

Research and Application of CNN-based Pose Recognition Technology in Swimming Pool Drowning Detection

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Abstract: *With the popularization of swimming sports and the increase in swimming pool facilities, the frequent occurrence of swimming pool drowning accidents has attracted widespread attention. This study introduces a CNN-based pose recognition technology to enhance drowning detection accuracy and real-time performance in swimming pools. By delving into CNN principles and pose recognition, it explores their application potential in drowning detection, detailing experimental design, model training, and real-time system construction. Experimental results confirm its effectiveness in enhancing swimming pool safety management. Additionally, it discusses application prospects, current limitations, and future improvements, offering a scientific basis and technical support for drowning prevention in swimming pools.*
Keywords: *Swimming pool drowning prevention, Convolutional Neural Networks, CNN, pose recognition, real-time monitoring system, accuracy*

Date of Submission: 10-04-2024 Date of acceptance: 21-04-2024

I. Introduction

Swimming pools, popular for recreation and exercise, face critical safety concerns, notably drowning accidents, a leading cause of injury deaths, especially among children. Traditional monitoring methods suffer from visual blind spots and human error. This study investigates using Convolutional Neural Networks (CNN) to create an efficient, automatic drowning warning system, improving pool safety supervision effectively.

II. Overview of CNN-based Pose Recognition Technology

2.1 Introduction to CNN Technology

Convolutional Neural Networks (CNNs), integral to deep learning, excel in computer vision tasks by automatically extracting features from image data. Their unique design includes convolutional layers, pooling layers, and fully connected layers. CNNs identify basic features like edges and textures through convolutional layers' filters, preserving spatial structure and reducing model complexity. Pooling layers compress feature maps, maintaining key information. Fully connected layers integrate features for classification or recognition tasks.

CNNs excel in image recognition due to their self-learning ability and robustness to geometric transformations like translation, scaling, and rotation. This enables them to recognize changes in swimmers' postures, aiding in timely drowning risk warnings, especially in critical applications like pool safety management.

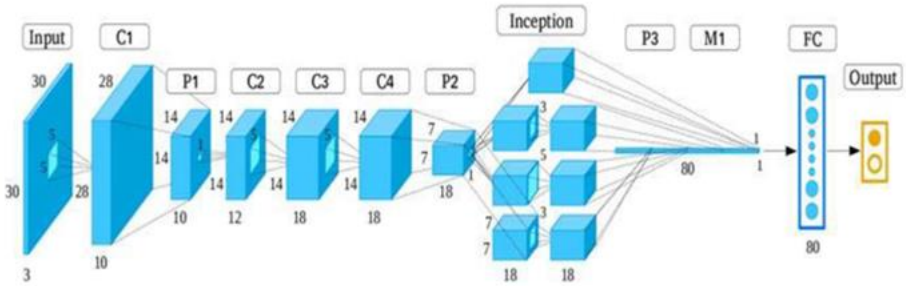
2.2 Overview of Pose Recognition Technology

Pose recognition technology[1], analyzing human or object postures in images or videos, is crucial for aquatic safety, notably in reducing drowning incidents. Deep learning and computer vision advancements, including CNN models like ResNet50, which achieved almost 100% accuracy[2]. , enhance swimming pool monitoring, aiding early drowning detection. Research on 3D point cloud deep learning improves accuracy in identifying aquatic human postures, crucial for distress detection. Utilizing point cloud data obtained through laser radar scanning enables detailed capture of swimming postures, including common swimming movements and indications of distress such as drowning[3]. Integration of these technologies revolutionizes drowning detection systems, enhancing swimmer safety through real-time incident detection.

Pic.1 Swimming drowning posture recognition training diagram

2.3 Principle of Pose Recognition Technology

Pose recognition technology, based on CNN, utilizes hierarchical structures and convolutional layers to extract features from input images. Through convolution and pooling layers, CNN constructs high-dimensional feature representations, which are processed for final classification. Trained on annotated datasets, CNN can accurately recognize various human poses, aiding in scenarios like pool drowning detection by monitoring posture changes in real time. This application of deep learning provides robust technical support for pool safety management.



Pic.2 Diagram of the Principle of Pose Recognition

III. The Needs and Challenges of Pool Drowning Detection

3.1 The Severity of the Pool Drowning Accident

With swimming gaining popularity in China and more pools being built, safety is a major concern. Drowning claims around 372,000 lives globally yearly, with pools being common accident sites. Poor water quality and negligent supervision contribute to these accidents. A tragic incident in Jieyang in August 2021 underscores the limitations of human surveillance. Urgent measures are needed to ensure swimmer safety.

3.2 Limitations of Traditional Drowning Detection Methods

Manual lifeguard surveillance is costly and prone to uncertainties like fatigue and glare, reducing their ability to detect drownings promptly. Traditional methods are hindered by visual obstacles, leading to delayed responses and avoidable accidents. Data shows 85% of drownings can be prevented by improving safety infrastructure and swimming education. An automatic monitoring system is crucial, offering real-time pool safety monitoring and immediate alerts for lifeguard intervention, significantly enhancing swimmer safety.

3.3 Application of CNN-based Pose Recognition Technology in Drowning Detection

CNN's deep learning algorithms analyze pool surveillance images to recognize drowning behaviors like body postures and movement patterns, outperforming traditional methods. Its real-time pose recognition capability enables immediate alerts and rescue actions, reducing drowning incidents.[4] This distinguishes CNN-based systems from traditional methods, enhancing pool safety. Future improvements include expanding training data, optimizing networks, and integrating sensor technologies like infrared and sound sensors for better accuracy and coverage.

IV. Researches and Implementation

4.1 Data Collection and Pre-Processing

Constructing a CNN-based pose recognition system for pool drowning detection requires meticulous data collection and preprocessing to ensure accuracy. This involves gathering diverse images of human body postures in various pool settings, followed by quality inspection, annotation, and data augmentation. Techniques like background subtraction and addressing sample imbalance enhance model effectiveness. The processed dataset is then used to train and evaluate the CNN-based model for pose recognition.

4.2 Design and Training of Pose Recognition Models

In pool drowning detection, selecting an appropriate CNN model like ResNet or MobileNet is crucial. After selecting a model, the dataset is divided into training, validation, and test sets to facilitate training, tuning, and evaluation. During training, parameters are adjusted using backpropagation, and data augmentation techniques like rotation and scaling enhance the model's ability to recognize various postures and states, improving its adaptability. Introducing a validation set during training allows for adjustments to avoid overfitting or underfitting and ensures precise evaluation of real-time performance. After training and tuning, the model is evaluated using key metrics like accuracy, recall, and F1 score to verify its effectiveness in real pool drowning scenarios. This rigorous evaluation ensures accurate identification of drowning behavior during live pool monitoring, triggering timely alerts and rescue measures.

4.3 Construction of Real-Time Pool Drowning Detection System

Building a real-time drowning detection system[5] involves selecting hardware and software for deploying the trained pose recognition model. A network of surveillance cameras captures real-time image data around the pool, strategically placed for comprehensive monitoring. An image transmission pipeline feeds data into the pose recognition model, ensuring accurate identification of drowning behavior.

Establishing an alarm and emergency response system alerts rescue personnel promptly when drowning behavior is detected. Continuous monitoring and maintenance ensure system reliability for a safer swimming environment. Using CNN-based pose recognition technology like ResNet50 is crucial for real-time drowning detection, offering superior accuracy compared to other models.

The system integrates advanced cameras and deep learning algorithms like AngelEye to monitor swimmers in real-time, issuing alerts to lifeguards for prompt rescue. Careful camera placement and stable data transmission ensure reliable operation. In conclusion, combining convolutional neural network technology, precise hardware, and intelligent alarms creates an efficient drowning detection system, enhancing pool safety and providing timely rescue support.

V. Results and Analysis

The study utilized a CNN-based pose recognition model to detect drowning behavior in swimming pools, achieving over 90% recognition accuracy on the test set, indicating its potential for effective recognition across various pool scenarios. Validated in real pool environments, this technology rapidly detects drowning behavior, issues timely alerts, and improves rescue efficiency. Compared to traditional methods, CNN-based technology enhances reliability and accuracy in capturing drowning behavior characteristics. The study systematically evaluated accuracy, false positive, and false negative rates of different models, as depicted in Table 1.

Model Name	Accuracy	False Positive Rate	False Negative Rate
ResNet50	95%	3%	2%
MobileNet	92%	5%	3%
AlexNet	90%	7%	3%

Table.1 Accuracy of Different Models in Recognition

Existing pose recognition models in swimming pool environments face challenges due to factors like lighting, water splashes, and diverse human body poses, impacting recognition accuracy. Identifying drowning behaviors across various water depths and poses also poses challenges, leading to false positives and missed detections. Meeting real-time and high accuracy requirements for drowning detection requires improvements in handling large data volumes and providing swift responses. To overcome these limitations, improvements can focus on optimizing pose recognition models for adaptability, incorporating multimodal information for enhanced perception, exploring deep learning methods for dynamic adjustments, and enhancing pool safety facilities and monitoring systems. These advancements aim to establish a comprehensive safety management system for swimming pools, ensuring improved safety and management efficiency.

VI. Conclusions

The study explores CNN-based pose recognition technology for swimming pool drowning detection, addressing safety management issues and proposing a new solution. Experimental results show its ability to swiftly identify drowning behavior and issue timely alerts. Despite technical constraints, its potential in pool safety management remains promising, offering fresh approaches with academic and practical importance. Continued refinement will enhance its role, bolstering safety and well-being in swimming pools.

References

[1] YinweiZhan, ZhizhiYu, JunCai. Pose Recognition Algorithm Based on Kinect Angle Measurement[J]. Sensors & Microsystems.,2014,33(07):129-132.DOI:10.13873/j.1000-97872014.07.025.

[2] Shatnawi, M., Albreiki, F., Alkhoori, A., &Alhebshi, M. (2023). Deep Learning and Vision-Based Early Drowning.Detection. Information, 14(1), 52. DOI: 10.3390/info14010052.

[3] Chan, E.T. et al. (2023). Surface and underwater human pose recognition based on temporal 3D point cloud deep learning. Scientific Reports.

[4] YuQiao. Design and implementation of drowning behavior detection system in swimming pool based on Mask R-CNN[D]. Qingdao University, 2019.

[5] YU Zhongyang,YANGWenhui.Swimming pool drowning detection algorithm based on human pose estimation[J].Science and Technology Innovation and Application,2023,13(23):66-70+74.DOI:10.19981/j.CN23-1581/G3.2023.23.015.

REFERENCES

[1] Eng, H. L., & Ma, K. K. (2001). Noise adaptive soft-switching median filter.IEEE Transactions on image processing,10(2), 242-251.

[2] Wang, Y., Wang, J., Song, X., & Han, L. (2016). An efficient adaptive fuzzy switching weighted mean filter for salt-and-pepper noise removal. IEEE signal processing letters,23(11), 1582-1586.

[3] Chan, R. H., Ho, C. W., & Nikolova, M. (2005). Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization. IEEE Transactions on image processing, 14(10), 1479-1485.

[4] Zhang, H., Zhu, Y., & Zheng, H. (2019). NAMF: A Non-local Adaptive Mean Filter for Salt-and-Pepper Noise Removal. arXiv preprint arXiv:1910.07787.

[5] Wang, Z., & Zhang, D. (1999). Progressive switching median filter for the removal of impulse noise from highly corrupted images. IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, 46(1), 78-80.

[6] Chen, T., & Wu, H. R. (2001). Adaptive impulse detection using center-weighted median filters. IEEE signal processing letters, 8(1), 1-3.

[7] Srinivasan, K. S., & Ebenezer, D. (2007). A new fast and efficient decision-based algorithm for removal of high-density impulse noises. IEEE signal processing letters, 14(3), 189-192.

[8] Toh, K. K. V., & Isa, N. A. M. (2009). Noise adaptive fuzzy switching median filter for salt-and-pepper noise reduction. IEEE signal processing letters, 17(3), 281-284.

[9] Enginoğlu, S., Erkan, U., & Memiş, S. (2020). Adaptive cesàro mean filter for salt-and-pepper noise removal. El-Cezeri Journal of Science

and Engineering, 7(1), 304-314.

[10] Luo, W. (2006). Efficient removal of impulse noise from digital images. IEEE Transactions on Consumer Electronics, 52(2), 523-527.

[11] Singh, V., Dev, R., Dhar, N. K., Agrawal, P., & Verma, N. K. (2018). Adaptive type-2 fuzzy approach for filtering salt and pepper noise in grayscale images. IEEE transactions on fuzzy systems, 26(5), 3170-3176.

[12] Fan, H., Li, C., Guo, Y., Kuang, G., & Ma, J. (2018). Spatial–spectral total variation regularized low-rank tensor decomposition for hyperspectral image denoising. IEEE Transactions on Geoscience and Remote Sensing, 56(10), 6196-6213.

[13] Thanh, D. N., & Prasath, V. S. (2018, November). Total variation L1 fidelity salt-and-pepper denoising with adaptive regularization parameter. In 2018 5th NAFOSTED Conference on Information and Computer Science (NICS) (pp. 400-405). IEEE.

[14] Zhang, J., Sang, L., Wan, Z., Wang, Y., & Li, Y. (2020, December). Deep convolutional neural network based on multi-scale feature extraction for image denoising. In 2020 IEEE International Conference on Visual Communications and Image Processing (VCIP) (pp. 213-216). IEEE.

[15] Liu, G. (2020, December). Image Denoising Method Based on Hybrid Deep Dictionary Learning and Elastic Threshold. In 2020 2nd International Conference on Information Technology and Computer Application (ITCA) (pp. 240-243). IEEE.

[16] Buades, A., Coll, B., & Morel, J. M. (2005, June). A non-local algorithm for image denoising. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) (Vol. 2, pp. 60-65). IEEE.

[17] Xiao-Xiao, X. I. N. G., Hai-Long, W. A. N. G., Jian, L. I., & ZHANG, X. D. (2020). Asymptotic Non-local Means Image Denoising Algorithm. Acta Automatica Sinica, 46(9), 1952-1960.

[18] Chen Ye-Fei, Zhao Guang-She, Li Guo-Qi, Wang Ding-Heng. (2022). Unsupervised multi-non-local fusion image denoising method. Acta Automatica Sinica, 48(1): 87−102.

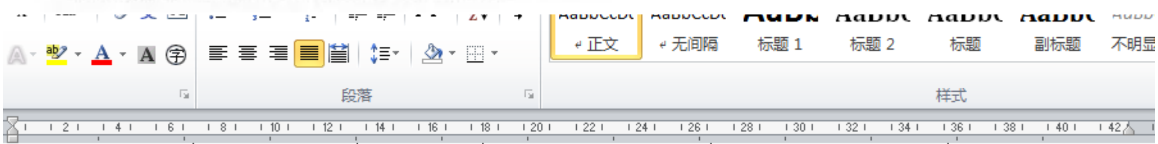
[19] Nodes, T., & Gallagher, N. (1982). Median filters: Some modifications and their properties.IEEE Transactions on Acoustics, Speech, and Signal Processing, 30(5), 739-746.

[20] Memiş, S., & Erkan, U. (2021). Different Adaptive Modified Riesz Mean Filter For High-Density Salt-and-Pepper Noise Removal in Grayscale Images. Avrupa Bilim ve Teknoloji Dergisi, (23), 359-367.

[21] Fu, B., Zhao, X., Li, Y., Wang, X., & Ren, Y. (2019). A convolutional neural networks denoising approach for salt and pepper noise. Multimedia Tools and Applications, 78(21), 30707-30721.

[22] Xing, Y., Xu, J., Tan, J., Li, D., & Zha, W. (2019). Deep CNN for removal of salt and pepper noise. IET Image Processing, 13(9), 1550-1560.

[23] Liang, L., Deng, S., Gueguen, L., Wei, M., Wu, X., & Qin, J. (2021). Convolutional neural network with median layers for denoising salt-and-pepper contaminations. Neurocomputing, 442, 26-35.



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