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Exploring Ear Recognition: Image Fusion and Deep Learning with Thermal and Visible Images

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Abstract - This pioneering study delves into the realm of ear recognition, introducing an innovative methodology that combines thermal and visible ear images using sophisticated multiresolution analysis, including discrete wavelet, ridgelet, and curvelet transforms. Our tailored deep learning model, uniquely designed for ear recognition, showcases outstanding results, with the complex-valued curvelet transform paired with thermal images achieving an impressive 96.82% recognition rate—outperforming all other methods. Notably, this research underscores the transformative impact of multi-source data fusion on elevating the effectiveness of ear recognition systems.

***Key Words*:** ridgelet, curvelet, effectiveness, multiresolution, pioneering

1.INTRODUCTION

Biometrics refer to biological measurements or physical traits for individual identification. These can be chemical (e.g., DNA), physical (e.g., fingerprints), or behavioral (e.g., gait). These unique features, like a signature, provide stability and quick results but may be deemed invasive, leading to discomfort in sharing personal information. Despite advantages, the perceived drawbacks include installation, operation, and maintenance costs. Nonetheless, biometric systems hold the distinctive capability to recognize personal characteristics in diverse applications.

1.1 THE SIGNIFICANCE OF EAR RECOGNITION:

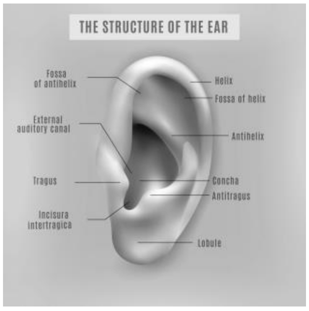

Figure-1-The Structure of The Ear

Biometric identification methods have evolved beyond traditional fingerprint and facial recognition systems. Ear recognition offers unique advantages, as the shape and features of the ear are distinct and stable over time. Moreover, ear recognition can be effective in scenarios where other biometric modalities may face challenges, such as low lighting conditions or partial facial obstructions.

1.2 IMAGE FUSION IN EAR RECOGNITION:

One of the key challenges in biometric recognition systems is dealing with varying environmental conditions. Image fusion, the process of combining information from multiple sources, has proven to be a valuable approach in overcoming these challenges. In the context of ear recognition, the fusion of thermal and visible images holds promise. Thermal imaging captures the heat patterns emitted by the ear, providing valuable information that is complementary to the visual characteristics captured by visible light imaging. By fusing these modalities, researchers aim to create a more robust and reliable ear recognition system that can perform effectively in diverse environments.

1.3 DEEP LEARNING FOR FEATURE EXTRACTION:

Deep learning, particularly convolutional neural networks (CNNs), has revolutionized the field of image processing and pattern recognition. In ear recognition, deep learning plays a crucial role in automatically extracting discriminative features from fused thermal and visible images. By training neural networks on large datasets of ear images, these models can learn intricate patterns and representations that are challenging to define manually. This automated feature extraction significantly improves the accuracy and generalization capabilities of ear recognition systems, making them adaptable to various scenarios.

Apart from widely-used biometric systems like fingerprints, iris, retina, and face recognition, ear recognition has gained attention due to its distinctive features. Iannarelli (1989) initially demonstrated the uniqueness of ear structures through manual measurements, highlighting differences among individuals. However, applying this method practically is challenging. Recent studies have focused on automating ear recognition, extracting new features, and developing effective methods for real-world applications.

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Ear recognition stands out for its versatility as ear images can be easily captured from profiles or videos, unlike fingerprint and iris recognition requiring direct sensor interaction. This non-intrusive approach allows remote image acquisition without subject cooperation, aligning with face and palm recognition methods. Notably, even identical twins exhibit differences in ear structure features . Ear recognition complements other modalities, aiding identification in unreliable or unavailable information scenarios in multimodal biometric systems.Despite its advantages, ear recognition faces challenges, with illumination levels impacting the recognition process. Illumination issues, common in biometric applications like ear and face recognition, require adaptive methods for effective ear biometry . An active approach, as demonstrated by Abaza & Bourlai (2012), adapts to varying illumination conditions by utilizing imaging modalities independent of illumination. Their method showedpromising results in both mid-wave infrared (MWIR) and visible bands, combining the advantages of each spectrum—immunity to illumination variations in thermal imaging and effective texture feature representation in visible images illuminated with sufficient light. This study effectively merged thermal and visible images to harness comprehensive information.

In the symphony of identification, ear recognition takes center stage, choreographed manually or with the finesse of automation. Bertillon (1896) initiated the ear's solo, showcasing its individuality. Iannarelli's magnum opus in 1989, a visual masterpiece with over ten thousand ear images, paved the way for the automatic encore. The 1990s witnessed geometric ballet, ear sonata through Principal Components Analysis (PCA), and (2010) recognition waltz, achieving a 97.5% success rate by elegantly segmenting ear images into 12 modules with captivating preprocessing.In (2014) comprehensive study unfolded like a dramatic opera, with Linear Discriminant Analysis hitting the right notes using various feature extraction methods. In the grand finale, the avant-garde era embraced deep learning, with leading the ensemble. Convolutional Neural Networks (CNNs) became the virtuosos, gracefully navigating the nuances of shape and visual variations, eliminating the need for separate algorithms. This marks not just a leap but a pirouette in the mesmerizing world of automatic ear recognition.

In the realm of automatic ear recognition, deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a star performer. Contrasting with traditional methods like Local Binary Patterns (LBP) (or Histogram of Oriented Gradients (HOG) , CNNs showcase heightened robustness and tolerance to shape and visual variations in images designated for recognition . The magic lies in CNNs' convolution layers autonomously extracting features, obviating the need for separate feature extraction algorithms.A symphony of ear recognition, comparing manually crafted and CNN-based models. They extracted features through seven methods, classified them with Support Vector Machines (SVM), and then unleashed the power of AlexNet, a CNN architecture. The results sang a compelling tune, with AlexNet achieving a 22% higher success rate. This harmony resonates in other studies leveraging AlexNet architecture. In a different composition, orchestrated high accuracy rates, even with limited training data, using diverse CNN architectures like VGG-16 and SqueezeNet.

El Naggar & Bourlai (2022) showcased remarkable success rates, achieving 98.76% for visible and 96.93% for thermal images using pre-trained CNN architectures and transfer learning on consistent lighting conditions across various ear datasets. These results collectively emphasize the consistent superiority of deep learning over feature extraction-based methods in ear recognition applications.

While face recognition studies have effectively addressed illumination challenges through thermal and visible image fusion , limited research explores this fusion for ear recognition. This path, employing simple fusion rules and the Histogram of Oriented Gradients (HOG) method, coupled with SVM classification, reporting enhanced results. In our study, we ventured differently, merging thermal and visible ear images using Multiresolution Analysis (MRA) methods. Unprecedentedly, no prior research has combined these images with MRA and classified them using deep learning methods. Our study's findings mark a significant stride in advancing the realm of ear recognition.

This study utilized the DIAST dataset, incorporating both thermal and visible ear images. Employing various Multiresolution Analysis (MRA) techniques, we fused thermal and visible ear images. The resulting amalgamated images were then utilized to train and evaluate the performance of our tailor-made CNN model. Experimental studies were conducted under diverse illumination conditions, assessing the effectiveness of our proposed method. Recognition rates were calculated to gauge its performance across different modalities. In summary, the key contributions of this study are the integration of MRA techniques for image fusion and the development of a custom CNN model, showcasing robust performance under varied illumination conditions in the context of ear recognition.

1.4 THE KEY CONTRIBUTIONS OF THIS STUDY CAN BE SUMMARIZED AS FOLLOWS:

1.4.1 MRA-BASED FUSION:

Three distinct Multiresolution Analysis (MRA) methods were employed for image fusion, enabling the capture and amalgamation of distinctive features present in thermal and visible ear images acquired under varying illumination conditions.

These fusion techniques excel in preserving details, showcase improved generalization capabilities, and deliver superior visual results.

1.4.2 UNIQUE CNN MODEL:

A specialized CNN model was meticulously designed to extract ear features from the fused images. Remarkably, this model demonstrated outstanding results, achieving high performance with a minimal number of parameters, despite the constraints of limited available data.

1.4.3 ENHANCED RECOGNITION:

The results emphasize a substantial improvement in the success of ear recognition applications through the fusion process. This performance boost is particularly noteworthy when tackling variations in illumination conditions.

Essentially, our study underscores the potential of MRA-based fusion techniques paired with a carefully designed CNN model to notably enhance the effectiveness of ear recognition. This is especially evident in challenging scenarios marked by varying illumination levels.

2 EXISTING METHODOLOGY:

2.1 CASE STUDY 1: MULTIMODAL FUSION FOR ACCESS CONTROL IN HARSH ENVIRONMENTS

In a high-security facility, where traditional biometric methods faced challenges due to varying lighting conditions and potential obstructions, researchers implemented a multimodal ear recognition system. This system fused thermal and visible images, allowing for reliable identification even in low-light and challenging environmental conditions. The integration of deep learning algorithms for feature extraction improved the accuracy of access control, ensuring a more robust security solution.

2.2 CASE STUDY 2: HEALTHCARE AUTHENTICATION USING THERMAL AND VISIBLE EAR IMAGES

In a healthcare setting, where hygiene is crucial, a biometric authentication system was developed using ear recognition. By incorporating both thermal and visible images, the system addressed concerns related to varying patient conditions and lighting in medical environments. Deep learning models were trained on a diverse dataset, enabling the system to adapt to different patient profiles. This approach streamlined authentication processes, enhancing patient data security while maintaining convenience for medical staff.

2.3 CASE STUDY 3: EAR RECOGNITION FOR LAW ENFORCEMENT APPLICATIONS

Law enforcement agencies sought a biometric solution that could reliably identify individuals in surveillance footage, even when facial features were obscured. A multimodal ear recognition system was implemented, combining thermal and visible images. Deep learning algorithms were trained to detect and recognize unique ear features, aiding in suspect identification. This approach provided a valuable tool for law enforcement in scenarios where traditional facial recognition methods might fail.

2.4 CASE STUDY 4: WORKPLACE SECURITY WITH THERMAL-VISIBLE EAR RECOGNITION

In a corporate environment with strict access control requirements, a novel ear recognition system was deployed. By fusing thermal and visible images, the system offered heightened security in various lighting conditions and weather conditions outside the building. Deep learning models were trained to adapt to the diverse workforce, ensuring accurate and efficient access control. The system proved effective in enhancing workplace security without compromising user convenience.

These case studies illustrate the versatility and practical applications of ear recognition systems that leverage image fusion and deep learning. From high-security facilities to healthcare and law enforcement, these technologies are proving instrumental in overcoming challenges posed by traditional biometric methods.

3 PROPOSED METHODOLOGIES:

Creating a system for automatic class determination in fusion images involves several steps. First, gather a dataset with thermal and visible ear images under diverse lighting conditions. Implement a CNN model, incorporating Multiresolution analysis methods for feature extraction. Train the model using the dataset, ensuring proper validation. Fine-tune hyperparameters for optimal performance. Evaluate the model on a test set and refine as needed. Document your methodology and results for comprehensive understanding.

3.1 THIS SECTION COMPRISES THREE SEPARATE SUB-STEPS:

1. Multiresolution analysis method,
2. Pixel-level fusion of thermal and visible ear images, and
3. The designed convolutional neural network Model and parameters.

3.1.1 MULTIRESOLUTION ANALYSIS METHOD:

In the enchanting realm of image processing, the advent of wavelets has bestowed Multiresolution Analysis (MRA) with a crown of popularity (Cihan & Ceylan, 2021). Operating gracefully at various scales, MRA serves as the sorcerer's wand, conjuring the latent features of images into view. By revealing images in a symphony of scales, subtle nuances become visible, dancing across the canvas of perception. Within the mystical confines of this study, three MRA enchanters took center stage discrete wavelet transform, ridgelet transform, and curvelet transform. Like magical artisans, these methods wove together thermal and visible images into a tapestry of fusion. With an innate ability to decipher points, edges, and curves, these mystical methods are sought after for the alchemy of tasks like image denoising, object recognition, and the sacred art of image fusion. Moreover, each method whispers secrets through different levels and versions of transformation, ensuring a spellbinding journey through the world of visual incantations.

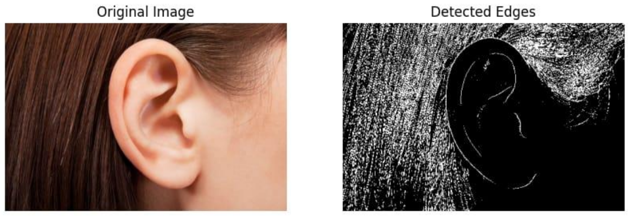

Figure-2-Multiresolution Analysis Method

3.1.2DISCRETE WAVELET TRANSFORM (DWT):

One of the MRA techniques used to analyze stationary and non-stationary data is the Wavelet Transform. It is a useful tool for image analysis techniques since it allows for local analysis by breaking down data into different frequency components. This division makes it possible to examine big signals in constrained spaces . The 2D-DWT procedure using low-pass and high-pass filter banks is shown in Figure 1. Through this technique, images with detail coefficients (HL, LH, and HH subbands) that transmit more information are produced, along with their low-resolution counterpart (LL subband), which carries the approximation coefficients. To reach further levels of transformation, the LL subband might undergo additional transformation.

Equation is used to apply WT in discrete form, where i, wi, si, pi and Ψ(t) are the numbers of the samples, weight coefficients, scales, positions and mother wavelet, respectively.

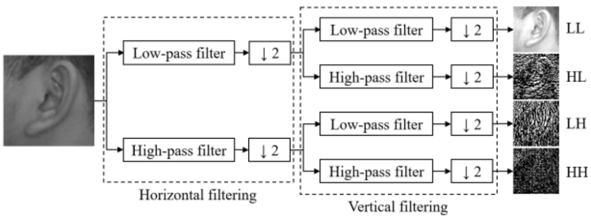

Figure-3-Discrete wavelet transform Method

3.1.3 PIXEL-LEVEL FUSION OF THERMAL AND VISIBLE EAR IMAGES:

Embark on the captivating journey of image fusion, a mystical art that weaves together the tapestry of diverse sensor-captured visions. This enchanting process harmonizes images from different sensors, unveiling the hidden facets that each alone could not reveal. Imagine datasets as a treasure trove, each holding unique information, collected under the watchful gaze of different sensors and ever-changing conditions.

In the realm of computer vision, image fusion emerges as the alchemist's brew, distilling critical information from multiple images into a singular, enriched masterpiece. Picture it as a symphony of pixels and Multiresolution Analysis (MRA) methods, orchestrating a visual feast. The resulting fused image, an alchemical concoction, transcends the limitations of individual input images, offering a captivating narrative of the unseen .Venture into the echoes of past studies, where explorers delved into the artistry of pixel-level fusion and the mesmerizing Multiresolution Analysis methods, penned by visionaries like Pajares & De La Cruz . The canvas of image fusion beckons, promising a journey through pixels, waves, and the magic of uncovering the extraordinary within the ordinary.

$$F = (T + V)/2 \qquad (2)$$

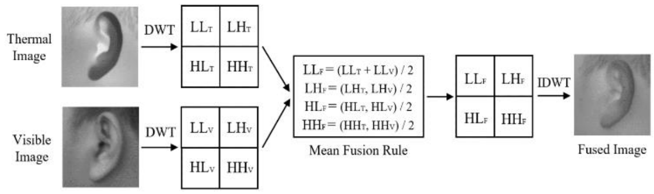

Figure-4-Pixel-level fusion Technique

3.1.4 THE DESIGNED CONVOLUTIONAL NEURAL NETWORK MODEL AND PARAMETERS:

Dive into the captivating realm of Convolutional Neural Networks (CNNs), those mystical architects within the grand tapestry of deep neural networks. Much like specialized sorcerers among multilayer perceptrons, CNNs wield their magic across diverse landscapes, leaving their mark in realms such as enchanting image classification , the healing artistry of medical image analysis , the dance of pixels in image clustering , and the keen-eyed gaze of object recognition.

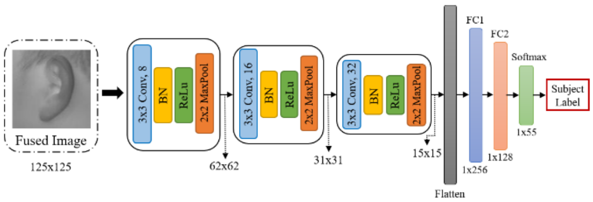

Figure-5- Convolutional Neural Network method

Behold the spellbinding architecture of a typical CNN—a symphony of components interwoven like threads of fate. Picture the convolution layer as the alchemist's cauldron, where raw information undergoes transformation. A pooling layer, akin to a shimmering pool of knowledge, distills and refines. The activation function, the spark of magic, imbues layers with life and meaning. Finally, the fully connected (FC) layer weaves these elements into a tapestry of understanding, completing the neural network masterpiece. Let your imagination traverse the neural pathways, where each layer of the CNN dances in harmony, unveiling the secrets of pixels, patterns, and the mesmerizing artistry of intelligent perception.

4 EXPERIMENTAL SETUP AND RESULTS:

Let's take a stroll through the data world. First, we'll get to know the dataset. Then, we blend thermal and visible ear images using some cool MRA-based fusion methods we talked about earlier. These mixed-up images become the training material for our specially crafted CNN model.Imagine the CNN model as a conductor, making sense of this blend of images. Now, we move to the experiment phase, where we see what happens. The results and discoveries come out, like finding patterns in a puzzle. We share and chat about what we found in those mixed-up ear images, making it a bit like telling a story about what the computer learned from them.

4.1 DATASET:

In our research, we worked with the DIAST dataset, as explained by Ariffin et al. (2016). This dataset is like a treasure trove containing both thermal and visible ear images—2200 in total, from 55 different folks. For each person, there are 1100 thermal and 1100 visible ear images, covering both left and right ears. These raw images are grayscale, saved as jpg files, and measure 125x125 pixels.What makes this dataset special is the variety of lighting conditions it captures. Each person's ear images were taken under five different lighting levels, ranging from a dim 2 lux to a bright 10700 lux. We grouped these images into three lighting conditions: 'dark' for lux values up to 20, 'average' for lux values between 21 and 100, and 'bright' for lux values over 100. To make it more vivid, check out Figure —it gives you a glimpse of example images captured under different lighting conditions.

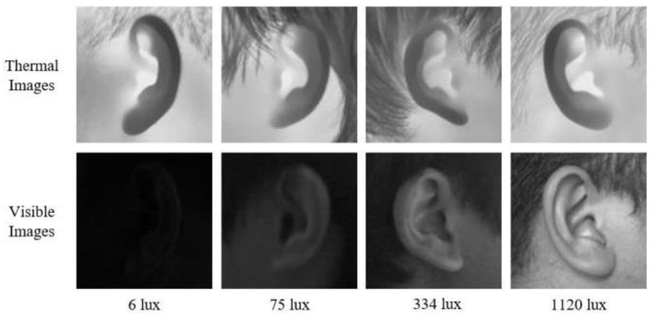

Figure-6- Result using Thermal Image & Visible Image

4.2 CHALLENGES AND FUTURE DIRECTIONS:

Despite the advancements, challenges remain in the integration of thermal and visible images for ear recognition. Issues such as image misalignment, sensor noise, and limited datasets for training deep learning models are areas of ongoing research. The future of ear recognition lies in refining these techniques and addressing current challenges. Researchers are actively exploring novel algorithms, incorporating additional modalities, and expanding datasets to enhance the robustness and reliability of ear recognition systems.

5 CONCLUSION

The performances achieved through the mean fusion rule, utilizing three MRA methods (DWT, RT, CT), were compared in the proposed ear recognition system. Furthermore, the impact of thermal and visible images on performance under various illumination conditions was assessed. The ensuing results are presented as follows:

Thermal imaging remains resilient to illumination variations but encounters difficulty capturing texture properties. On the other hand, well-illuminated visible images excel at capturing textures. To leverage the strengths of both modalities without sacrificing information, we employ appropriate fusion techniques. This fusion amalgamates the distinctive features of thermal and visible images, resulting in successful outcomes.

During the training of the CNN model with dark images, visible images demonstrate lower recognition performance compared to thermal and fusion images.CCT emerges as the star player in our MRA lineup for ear recognition, stealing the spotlight with impressive recognition rates. Its prowess lies in capturing the nuances of directional selectivity in ear images, cleverly leveraging both phase and amplitude information. Picture this: thermal images take the lead for the right ear's recognition, while CCT claims the throne for the left ear's highest recognition rate. Adding a dash of excitement, both RCT and 3-level DWT join the party with stellar recognition rates for both the right and left ears. These findings paint a vivid canvas of how ear recognition gets a turbo boost through our fusion process. Yet, here's the plot twist – there's no one-size-fits-all fusion technique for ear recognition; it's a fusion fiesta with choices.

In the realm of ear recognition, where data whispers rather than roars, our study orchestrates a symphony of innovation. With a limited ear dataset, we unveil the prowess of deep learning and image fusion techniques, turning data constraints into a captivating melody of high-quality results. These methods don't merely adapt; they redefine the rules, setting a stage for future research to dance with possibilities in this domain. The findings from our study resonate not just as answers but as inspiration, echoing through all fields grappling with the subtle art of data limitations.

Embarking on the next chapter of exploration, unfurling the dataset's boundaries and enriching the symphony of our study by training the CNN model with an expanded repertoire of data would be a harmonious progression. Imagine the stage adorned with CNN architectures like AlexNet, VGG, and SqueezeNet, each lending its unique rhythm to the melody of our findings. In this dance of discovery, the limited dataset's size becomes an invitation for pre-trained models to pirouette into the limelight, promising a quicker and more effective research performance.

Beyond the ordinary, let's dive into the kaleidoscope of fusion methods and rules. Each variation a stroke on the canvas of insights, offering a vibrant palette to paint the future of ear recognition research. The journey ahead holds the promise of not just expansion but a creative crescendo, where each added layer of complexity unveils new dimensions in the symphony of knowledge.

REFERENCES

[1]Abaza, A., & Bourlai, T. (2012, May). Human ear detection in the thermal infrared spectrum. In Thermosense: Thermal Infrared Applications XXXIV, 8354, 286-295. https://doi.org/10.1117/12.919285

[2]Alshazly, H., Linse, C., Barth, E., & Martinetz, T. (2019). Handcrafted versus CNN features for ear recognition. Symmetry, 11(12), 1493. https://doi.org/10.3390/sym11121493

[3]AlZubi, S., Sharif, M. S., Islam, N., & Abbod, M. (2011, May). Multi-resolution analysis using curvelet and wavelet transforms for medical imaging. In 2011 IEEE international symposium on medical measurements and applications, 188-191. DOI: 10.1109/MeMeA.2011.5966687

[4]Ariffin, S. M. Z. S. Z., Jamil, N., & Rahman, P. N. M. A. (2016, September). DIAST variability illuminated thermal and visible ear images datasets. In 2016 Signal Processing:

[5]Algorithms, Architectures, Arrangements, and Applications (SPA), 191-195. DOI: 10.1109/SPA.2016.7763611

[6]Ariffin, S. M. Z. S. Z., Jamil, N., & Rahman, P. N. M. A. (2017, May). Can thermal and visible image fusion improves ear recognition?. In 2017 8th International Conference on Information Technology (ICIT), 780-784. DOI: 10.1109/ICITECH.2017.8079945
[7]Abd Almisreb, A., Jamil, N., & Din, N. M. (2018, March). Utilizing AlexNet deep transfer learning for ear recognition. In 2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP), 1-5. DOI: 10.1109/INFRKM.2018.8464769
[8]Ashiq, F., Asif, M., Ahmad, M. B., Zafar, S., Masood, K., Mahmood, T., Mahmood, M. T., & Lee, I. H. (2022). CNN-based object recognition and tracking system to assist visually impaired people. IEEE Access, 10, 14819-14834. DOI: 10.1109/ACCESS.2022.3148036
[9]Benzaoui, A., Kheider, A., & Boukrouche, A. (2015, October). Ear description and recognition using ELBP and wavelets. In 2015 International Conference on Applied Research In Computer Science And Engineering (Icar), 1-6. DOI: 10.1109/ARCSE.2015.7338146
[10]Bertillon, A., & McClaughry, R. W. (1896). Signaletic instructions including the theory and practice of anthropometrical identification. Werner Company
[11]Candès, E. J., & Donoho, D. L. (1999). Ridgelets: A key to higher-dimensional intermittency?. Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 357(1760), 2495-2509. https://doi.org/10.1098/rsta.1999.0444
[12]Chen, D., Tang, J., Xi, H., & Zhao, X. (2021). Image Recognition of Modern Agricultural Fruit Maturity Based on Internet of Things. Traitement du Signal, 38(4). DOI: 10.18280/ts.380435
[13]El-Naggar, S., & Bourlai, T. (2022). Exploring Deep Learning Ear Recognition in Thermal Images. IEEE Transactions on Biometrics, Behavior, and Identity Science, 5(1), 64-75. DOI: 10.1109/TBIOM.2022.3218151

BIOGRAPHIES

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