A Review of Deep Learning-Based Feature Extraction Techniques for Iris Image Analysis

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Feature extraction is a critical process in image processing, directly influencing the accuracy of classification tasks. Traditional feature extraction methods often fall short by capturing only a limited set of features, which can result in suboptimal classification, particularly in complex biometric systems. In the domain of iris recognition, the extraction of minute and intricate features is paramount for achieving high accuracy and reliability. This paper presents a comprehensive review of advanced deep learning-based feature extraction techniques tailored for iris images. These techniques are designed to capture and process fine details such as lacunae, Wolfflin nodules, contraction furrows, and pigment spots—features that are essential for both recognition and diagnostic purposes. We compare state-of-the-art methods including convolutional neural networks (CNNs), U-Net, Link-Net and other custom architectures, highlighting their advantages in terms of segmentation precision, feature extraction efficiency, and computational requirements. Our review also addresses the challenges posed by variations in iris texture, illumination, and occlusions, which can affect the accuracy of feature extraction. Experimental evaluations of these methods show that deep learning algorithms significantly improve the detection of subtle features, offering promising results for both recognition accuracy and disease diagnosis applications. Finally, we outline future directions in the field, including the potential for integrating multi-resolution and attention-based models to further enhance the extraction of fine details from iris images. We also discuss the opportunities for real-time deployment of these techniques in mobile and resource-constrained environments, opening new avenues for iris recognition and diagnostic systems.

Povzetek: Pregledno so opisane so tehnike za ekstrakcijo lastnosti irisnih slik z uporabo globokega učenja, pri čemer so kombinirana konvolucijska nevronska omrežja (CNN) za obdelavo natančnih in subtilnih značilnosti, kot so lacune in pigmentne pike.

1 Introduction

Feature extraction is a fundamental step in data processing [1], designed to transform raw data into a manageable set of relevant features that capture the most significant information for a particular task. This process simplifies data by reducing its dimensionality, making it more efficient for analyzing machine learning models. In traditional methods, feature extraction relies on predefined techniques like edge detection [2], texture analysis, or frequency-domain transformations (e.g., Fourier or wavelet transforms), commonly used in areas such as image processing, audio analysis, and signal processing. These techniques highlight important characteristics of the data, such as edges or textures in images, which help in the classification or recognition tasks. Feature extraction is essential for improving computational efficiency, particularly when dealing with large datasets, as it reduces redundant information and helps models generalize better by focusing on the most critical aspects of the data [3].

Deep learning is a subset of machine learning that automates feature extraction through multi-layered neural networks. It is particularly effective for handling complex, high-dimensional datasets like images, videos, and text, where manually extracting features may be inefficient or impractical. The primary model in deep learning for feature extraction is the Convolutional Neural Network (CNN), which excels in image and video recognition tasks by learning hierarchical features from pixel-level data. CNNs automatically identify low-level features like edges and gradually learn more abstract features such as shapes and objects as data moves through deeper layers of the network. Recurrent Neural Networks (RNNs) are another type of deep learning model used for sequential data, like time series or language processing, where context over time is crucial. The advantage of deep learning models is that they can discover patterns without manual intervention, leading to state-of-the-art performance in fields such as computer vision, natural language processing, and medical image analysis [4].

In contrast to deep learning, traditional machine learning models, such as Support Vector Machines (SVM), decision trees, and k-nearest neighbors (KNN), rely on manually engineered features. These models work well when datasets are smaller and structured, with clear feature representations. While not as powerful as deep learning for unstructured data like images or text, traditional models are highly effective for simpler tasks and require less computational power. For example, decision trees and random forests can model decisions in structured environments, while SVMs are often used for classification tasks with well-defined input features [5]. These models are also more interpretable than deep learning networks, making them preferable when understanding model decisions is important. Feature extraction techniques in machine learning, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), help reduce dimensionality and ensure that models focus on the most informative aspects of the data.

Ultimately, deep learning emerges as the superior approach for feature extraction and analysis, especially in complex and high-dimensional datasets. Its ability to learn hierarchical representations directly from raw data without the need for manual feature engineering sets it apart from traditional machine learning techniques. Deep learning models, particularly CNNs, excel in extracting intricate patterns and features, making them highly effective for tasks like medical image analysis, where subtle details in data, such as those in iris images, can be critical for accurate diagnosis [6] and prediction. As computational resources continue to improve and large datasets become more accessible, the advantages of deep learning will likely expand further, solidifying its position as the best method for extracting meaningful insights from complex data. The below Fig. 1 represents the different features to be extracted from the enhanced iris image:

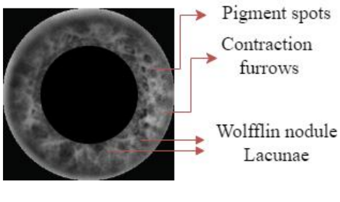

Figure 1: Iris features

2 Related works

2.1 Gradient-based feature extraction

After examining the impact of demosaicing on gradient extraction, Wei Zhou et al. [7] suggested a gradient-based feature extraction pipeline based on raw Bayer pattern images. In addition to consuming computing time, the traditional demosaicing method uses three times as much storage space in order to achieve almost identical results. However, by utilizing the color difference constancy assumption, the suggested method directly extracts gradients from the Bayer pattern images while lowering computing complexity. Five steps are involved in the SIFT-based algorithm's computation:

1) Constructing areas of scale. The difference-of-Gaussian (DoG) pyramid approximates the scale space.

2) The highest level of judgment. The local maxima and minima can be identified by comparing each pixel with its neighbors in a 3*3 neighborhood between the current scale, scale above, and scale below.

3) Locating the primary idea. to further hone the key point contenders discovered in the previous action. We discard unstable key points, such as places along edges with poor localization and low contrast.

4) Figuring out orientation. to offer one or more orientations for every significant point. A histogram is created for a region centered on the key point, with a radius 1.5 times the scale of the key point. The direction with the highest bar in the histogram is referred to as the dominating direction, whereas auxiliary directions are those with heights more than 80% of the top bar.

2.2 Feature fusion-net using deep spatial context encoder

A unique end-to-end Fusion-Net classification model for HR SAR images was proposed by Wenkai Liang [8]. Its goal is to fuse statistical characteristics into deep spatial feature objects in the end-to-end representation learning process. In a supervised feature learning framework, the physical characteristics of terrain objects can be revealed by the integration of distinct statistical distributions of SAR pictures into CNNs. In order to tackle this problem, a new end-to-end supervised classification technique is put forth for HR SAR images that takes statistical information and spatial context into account. Utilizing Fusion-Net has the benefit of enhancing the classification model's overall accuracy significantly through the complimentary knowledge of statistical and geographical variables. The definition of the Fusion-Net scheme is:

$$F^{Fuse} = sigm\left(W_2\left(sigm\left(GConv(W_1', F^{Spatial})\right)\right)\right.$$
$$\left.\left.\| \, sigm\left(GConv(W_1'', F^{Statistical})\right)\right)\right)$$

Compared to existing related systems, the suggested Fusion-Net produces substantially greater accuracies and a more pleasing visual look. This strategy yielded an overall accuracy of 89.00%. In the future, self-supervised learning techniques like contrastive learning or data augmentation like Mixup will be taken into consideration to improve DSCEN's feature representation capabilities.

2.3 Unsupervised deep image stitching

A two-stage unsupervised deep image stitching framework—unsupervised coarse image alignment and unsupervised image reconstruction—was presented by Lang Nie et al. [9]. Conventional feature-based picture stitching techniques frequently struggle to stitch images with low resolution or few features since they mostly rely on feature detection quality.

The suggested approach receives ratings of 27.83 and 0.902 for PSNR and SSIM, respectively. In terms of visual quality, people still prefer the outcomes of the suggested unsupervised approach over supervised deep image stitching alternatives. Furthermore, the reconstruction capacity is limited, indicating that the suggested approach could not work in situations with a very high parallax. Extending the linear deep homography to a non-linear homography model can help handle big parallax.

2.4 SpaSSA: Superpixelwise adaptive SSA

To utilize the local spatial information of HSI (Hyperspectral pictures), Genyun Sun et al. [10] presented SpaSSA (Superpixelwise adaptive Singular Spectral Analysis). While ignoring the local spatial context of the pixels, 2D-SSA primarily concentrates on global spatial information.

Improved classification accuracy can be achieved by using the suggested SpaSSA technique, which can successfully lower the intra-class variation within superpixels and improve the discriminating between various superpixels. This approach yields an overall accuracy of 98.34%. Principal component analysis and SpaSSA together can increase accuracy even more.

2.5 Symmetric all CNN (SACNN)

A symmetric all CNN (SACNN), an end-to-end network made up of encoder and decoder subnetworks, was proposed by Mingyang Zhang et al. [11]. Large numbers of labeled samples are always needed for deep learning network training, although HSI image data are rarely available. A unique unsupervised deep-learning based FE approach is developed to address this difficulty. The following is the definition of the cost function that the Adam algorithm optimizes:

$$L(X,R) = \frac{1}{P_1 Q_1 R_1}\sum_{i=1}^{P_1}\sum_{j=1}^{Q_1}\sum_{k=1}^{R_1}\left(x_{ijk} - r_{ijk}\right)^2 + \frac{\lambda}{2}\sum_{l=1}^{N}\sum_{i=1}^{P_2}\sum_{j=1}^{Q_2}\sum_{k=1}^{R_2}\left(w_{ijk}^{l}\right)^2$$

This approach yields an overall accuracy of 97.07%. The outcomes of the experiments indicated that learning effective spatial spectral features in HSI images was more suited for 3-D convolutional operation. Additional research will be conducted on adaptively optimizing hyperparameters based on data.

2.6 Spatial revising variational autoencoder-based feature extraction

Wenbo Yu et al. [12] introduced a novel unsupervised hyperspectral feature extraction architecture based on the spatial revising variational autoencoder (UHfeSRVAE). There are still several challenges in fully extracting rich spectrum information, such as the coupling of spectral and spatial information. To solve this issue, this approach makes use of designed networks to extract spatial characteristics from many perspectives in order to revise the spectral features that are subsequently obtained.

Compared to other methods, the suggested method yields a more accurate categorization map. The excellent clusterability and discernibility of UHfeSRVAE is further demonstrated by its performance in three-view drawings. This strategy yielded an overall accuracy of 91.39%. Additional research will concentrate on generative models for feature extraction.

2.7 Feature extraction via 3-D block characteristics sharing (3-D-BCS)

For high-strength images (HSI), Bing Tu et al. [13] suggested a unique feature extraction method using 3-D block characteristics sharing (3-D-BCS). The low sensitivity of sensors to spatial information and different environmental factors, such as weather, cause the neighboring spectral-spatial information of a pixel to become mixed in with other ground coverings. The following Fig. 2 is the suggested 3-D-BCS algorithm:

Algorithm 1 3-D-BCS

Inputs: Original HSI $\boldsymbol{I} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\} \in \mathbb{R}^{N\times M}$, Training set, and parameters setting: Q, S_N, K, and δ.
Outputs: Classification results obtained by decision fusion-based SVM classifier.
1: Obtain low-dimension HSI $\boldsymbol{D} = \{\boldsymbol{r}_1, \boldsymbol{r}_2, \ldots, \boldsymbol{r}_N\} \in \mathbb{R}^{N\times Q}$ by performing the MDS algorithm.
2: Generate nonoverlapping 3-D superpixel blocks by mapping $\boldsymbol{I}_s$ into the reduced image $\boldsymbol{D}$.
3: Block characteristic sharing-based feature extraction for each 3-D superpixel block.
4: **For** *each* $i = 1 : S_N$ **do**.
5: *Superpixel-based Gabor Filter*: Ensuring the texture consistency of each superpixel according to (14).
6: *Superpixel-based K-means Filter*: To address the spatial weak assumption within a superpixel, local density peak (15) and K nearest neighbor (16) are introduced.
7: *Superpixel-based Gaussian Weighting Filter*: Overcoming the spectral weak assumption among pixels within a superpixel according to (19).
8: **End For**
9: Superpixel Gabor feature-based SVM results.
10: Superpixel K-means feature-based SVM results.
11: Superpixel weighting feature-based SVM results.
12: Majority voting-based decision fusion for the classification results of the SVM classifier.

Figure 2: 3-D-BCS algorithm

This strategy yielded an overall accuracy of 96.69%. Tests conducted on many genuine hyperspectral data sets with a small number of training samples demonstrate that the suggested 3-D-BCS approach works better than alternative classification methods. The inability of single-scale over segmentation and single feature representation to fully mine the structural information of materials is one of the suggested method's limitations. Future research will focus on collaborative learning of multiscale strategies and numerous features for feature extraction.

2.8 Cloud-guided feature extraction approach

A cloud-guided feature extraction method was presented by Shangguang Wang et al. [14] for mobile image retrieval. Two main issues plague the current works: low retrieval accuracy and high network bandwidth costs.

Since the edge servers only upload the collected discriminative features to cloud servers, the suggested strategy can lower network traffic. This approach produced a retrieval accuracy of 88.33%. To dynamically update the projection matrix in the future, the model can be trained to extract the number of eigenvalues, accuracy, and reaction time.

2.9 Unsupervised structural feature-guided convolutional neural network (SFG)

Lin Ge et al. suggested an unsupervised structural feature-guided convolutional neural network (SFG) [15]. Gathering ground-truth data with known correspondences requires significant work and time when utilizing supervised algorithms. For this reason, unsupervised approaches are used. The two structural feature components of the proposed technique are sparse and dense structural components. The suggested method's pipeline looks like in the Fig.3:

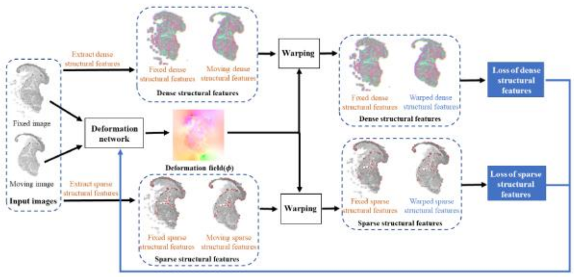

Figure 3: Unsupervised structural feature guided convolutional neural network Architecture

The network performs better when the two halves work together to fully utilize the global and local information in the histology picture. Additionally, it resolves the three issues with histology picture registration: section missing, repeating texture, and multiple staining. This technique, regardless of the entire scale or the expanded region of interest, satisfies several requirements for histological image registration. Furthermore, due of the severe damage to the structural feature, SFG is unable to conduct picture registration with significantly torn regions.

2.10 AFEM-Genetic algorithm

An ASC (Attribute Scattering center) feature extraction approach using genetic algorithm (AFEM-GA) was presented by Maoqiang Jing et al. [16]. This model is useful for inverse scattering problems and gives clear and physically meaningful features for complicated targets. The following is the suggested method's flowchart in Fig. 4:

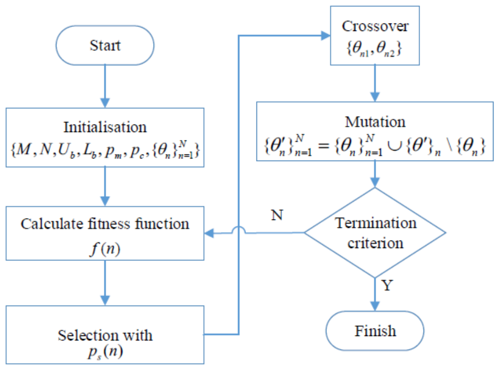

Figure 4: AFEM- Genetic algorithm flowchart

Compared to other methods, the suggested method is more computationally efficient since AFEM-GA does not require a large sparse dictionary. Improved AFEM-GA convergence speed and parallel estimate of all ASCs can be studied in more detail.

2.11 Gated stacked target-related autoencoder (GSTAE)

A gated stacked target-related autoencoder (GSTAE) was first presented by Qingqiang Sun et al. [17]. One of the most challenging problems in the world of image processing is still obtaining an appropriate feature representation from complex process data. In order to fairly take target-related information into account, the suggested STAE conducted a layer-wise pretraining process and incorporated the anticipated loss item of the target value into the original loss function of a common autoencoder.

The suggested method's drawbacks are that it becomes more computationally demanding and is susceptible to samples with low-quality labels. Therefore, it is crucial to remove low-value gate connections as soon as possible in order to minimize needless computational load.

2.12 Superpixel-based multiple statistical feature extraction (SPMSFE)

A unique multiple statistical feature extraction method based on superpixels was proposed by Dan Li et al. [18] (SPMSFE). This method was presented to increase the classification accuracies of hyperspectral images (HSIs), particularly when employing a small number of training samples. The suggested SPMSFE approach consisted of three steps: multiple statistical FE, multitask kernel sparse representation model for classification, and identification of superpixel-based neighbors. The suggested method's algorithm is as in Fig. 5:

The original HSI data set $\mathcal{X}$; number of dimensions l; number of superpixels L; threshold of the superpixel-based neighbors M.

Ensure:

1: Employ MNF on $\mathcal{X} \in \mathbb{R}^{s_1 \times s_2 \times d}$ to obtain the dimension-reduced data $\mathcal{F} \in \mathbb{R}^{s_1 \times s_2 \times l}$;
2: Generate 2-D superpixel map;
3: Identify the most similar superpixel-based neighbors for each pixel as $\mathbf{F}_i = [f_i^1, f_i^2, \ldots, f_i^{M'}] \in \mathbb{R}^{l \times M'}$;
4: Extract the mean feature $\boldsymbol{m}_i$, covariance descriptor $\mathbf{C}_i$, and Gaussian mixture feature $\mathbf{Y}_i$ for each pixel;
5: Utilize these three statistical features as the spatial–spectral features $\mathbf{Z}^r = [z_1^r, z_2^r, \ldots, z_n^r], r = 1, 2, 3.$;
6: Design the multiple kernels k_r using (13), (14), and (15) to map the multiple statistical features to the high-dimensional Hilbert space;
7: Randomly select N training samples to construct the directory $\mathbf{D}^r$ in the statistical feature space;
8: **for** each test pixel $z^r, r = 1, 2, 3.$ **do**
9: Obtain the sparse representation α^r based on Algorithm 1;
10: Calculate the reconstruction error of each class in a multitask model using (17);
11: Determine the class label of z^r using (18).
12: **end for**

Output: The result classification map

Figure 5: Superpixel-based multiple statistical feature extraction Algorithm

This strategy yielded an overall accuracy of 79.08%. The experimental results show that the suggested approach outperforms the most advanced classification techniques, especially in situations with a very small number of training examples. In order to handle the heterogeneous fusion of numerous statistical features and enhance performance, it will be necessary to examine the specific effects of each statistical feature for HSI images in depth in the future.

2.13 Superpixelwise PCA (S^3-PCA)

A unique spectral-spatial and superpixelwise PCA (S3-PCA) was proposed by Xin Zhang et al. [19]. This method effectively utilizes spatial information to extract the global-local and spectral spatial features for HSIs images and to remove noise via local reconstruction based on superpixels. The following is the suggested method's flowchart:

This technique is particularly useful for extracting useful features when working with noisy pixels in tiny, homogeneous regions. This strategy yielded an overall accuracy of 95.63%. Future work may integrate additional techniques like SVM and deep learning models, as superpixel-based local reconstruction has shown to be a successful filter for denoising high-spatiality images.

2.14 Layout feature extraction using CNN classification

Convolutional neural networks (CNNs) were used by Yoshikazu Nagamura [20] to categorize LSI layout photos in order to carry out the RCA of layout-induced errors. While predicting unknown flaws is a difficult task in the current study, analyzing layout-induced faults is essential to optimizing design rules. In order to extend the number of training datasets, this method addressed the limitation by chopping image clips at any place, including true defect positions. CNN models will eventually be trained on a tiny dataset of faulty layouts in order to forecast problems that are not yet known.

2.15 Fusion of deep learning-based features and empirical features

A fusion approach of merging adaptive characteristics generated by a deep neural network with empirical features was proposed by Jingsong Xie [21]. When dealing with objects that have low-quality training data, intelligent feature extraction and classification approaches cannot ensure that the model has learned the general characteristics needed for classification. Moreover, the model's robustness and generalization may be weak. This is a novel bearing fault classification technique built on top of XGBoost.

A few basic EFs and the adaptive features that LiftingNet extracted are combined to create the features that are utilized to train the XGBoost model[22] classifier. The suggested method's overall accuracy is 95.0%. The findings indicate that by combining a few EFs with the hidden features that the modified LiftingNet extracted, it is possible to enhance the model's accuracy and antinoise effect. Future research will concentrate on implementing the suggested approach in a variety of working environments [23].

Table 1: Summary of deep learning methods

S. No.	Title	Techniques/algorithms	Advantages	Disadvantages	Year
	A Cloud-Guided Feature Extraction Approach for Image Retrieval in Mobile Edge Computing	WAPL algorithm, projection matrix learning	- Reduces network traffic by 93% -Improves retrieval accuracy by 6.9% compared to the LBP algorithm	-	2019
	Unsupervised Hyperspectral Feature Extraction Using Variational Autoencoder	Variational Autoencoder (VAE), Deep Neural Networks (DNN), Local Linear Embedding (LLE), Autoencoder (AE), Segmented Stacked AE (S-SAE)	-Effective in extracting spectral-spatial features -High classification accuracy compared to pixel-wise methods - Utilizes both local and sequential sensing for better feature representation	- Increased computational time due to complex architecture - May not fully leverage spatial information in some methods	2020
	Feature Extraction via 3-D Block Characteristics Sharing for Hyperspectral Image Classification	3-D Block Classification System (3-D-BCS), Support Vector Machine (SVM), Structure-aware Collaborative Representation with Tikhonov Regularization (SaCRT), Joint Sparse Representation Classifier (JSRC), Enhanced Patch-based Filtering (EPF), Superpixel-based Classification via Multiple Kernels (SC-MK), Weighted Markov Random Fields	Improved classification accuracy, computational efficiency, and robustness across various datasets	Computational complexity due to Gabor filters and super pixel segmentation	2020

		(WMRF), Graph-based Deep Network (GFDN)			
	Symmetric All Convolutional Neural-Network-Based Unsupervised Feature Extraction for Hyperspectral Images Classification	3D Convolutional Neural Networks (3D-CNN), Encoder-Decoder Architecture	Unsupervised training reduces the need for labeled samples -Robust feature extraction for classification tasks -Effective in handling both spectral and spatial information	- Increased parameters may deteriorate feature quality - Requires careful tuning of the cost function to avoid overfitting	2020
	A Novel Bearing Fault Classification Method Based on XGBoost: The Fusion of Deep Learning-Based Features and Empirical Features	XGBoost, LiftingNet, PCA	-High classification accuracy (92%) compared to other methods (e.g., SVM: 88%) - Robustness to noise - Combines empirical features with deep learning for better decision-making	Requires some prior knowledge for empirical features	2020

	Gradient-Based Feature Extraction From Raw Bayer Pattern Images	Central difference gradient, HOG, SIFT	Efficient extraction from Bayer images, reduced need for demosaicing	Performance issues in complex textures	2021
	Unsupervised Deep Image Stitching Framework	Unsupervised coarse image alignment, unsupervised image reconstruction, ablation-based loss, stitching-domain transformer layer	Overcomes limitations of feature-based and supervised methods, suitable for large-baseline scenes, reduces space occupied by feature maps	Seam distortions, limited resolution in some cases	2021
	SpaSSA: Superpixelwise Adaptive SSA for Unsupervised Spatial-Spectral Feature Extraction in Hyperspectral Image	Superpixelwise Adaptive SSA (SpaSSA), 1DSSA, 2DSSA, PCA	-Reduces computational complexity and cost by operating on superpixels instead of full images. -Improves classification accuracy and efficiency in hyperspectral image analysis. -Adaptive window sizes enhance feature	- Sensitivity to window size can affect performance. - Lower accuracy on certain datasets like Pavia University due to ignored small ground	2021

			extraction.	features.	
	Attributed Scattering Center Extraction With Genetic Algorithm	Genetic Algorithm (GA)	Faster convergence speed due to floating-point encoding - Improved accuracy in parameter estimation	Computational cost increases with the number of parameters	2021
10	Superpixel-Based Multiple Statistical Feature Extraction Method for Classification of Hyperspectral Images	SPMSFE, MTKSRC, SSHGDA, SFMKSRC, LCMR, SRST, ISSR-DCNN, MCMs-2DCNN, S-DMM	-Superior classification accuracy (more than 3% higher OA value) -Faster computational speed compared to deep learning methods - Robustness with limited training samples	- Higher computational costs due to multiple statistical feature extraction - Gaussian distribution may not apply to all HSI data sets	2021
11	Layout Feature Extraction Using CNN Classification in Root Cause Analysis of LSI	Convolutional Neural Network (CNN), VGG16	-Superior classification ability for layout patterns -Capable of recognizing the local density of patterns -Can learn multiple layout patterns	- Requires a large amount of data for training -Low-resolution images may hinder	2021
	Defects		with different shapes	accurate defect prediction	
12	Unsupervised Histological Image Registration Using Structural Feature Guided Convolutional Neural Network	Structural Feature Guided Convolutional Neural Network (SFG)	Achieved the lowest Median rTRE among submissions to the ANHIR challenge; robust to multiple staining; integrates multi-scale structural features for better registration	AArTRE and AMrTRE are not the best due to challenges with extremely torn tissue sections; relies on automatic key point extraction which may not always be accurate	2022
13	GSTAE for Soft Sensing	STAE, GSTAE (Gated Stacked Autoencoder)	Improved prediction accuracy, especially for high-value samples -Better performance in soft sensing applications -Utilizes gated neurons for effective informati	Complexity in model structure due to multiple layers - Potential computational burden with increa	2022

			on flow control	sed layers	
14	Spectral-Spatial and Superpixelwise PCA for Unsupervised Feature Extraction of Hyperspectral Imagery	PCA, SuperPCA, S3-PCA	Achieves the best performance in terms of Overall Accuracy (OA), Average Accuracy (AA), and Kappa; effectively combines local and global features for improved classification	May neglect global information in small homogeneous regions or large regions with mixed ground truth objects	2022
15	A Feature Fusion-Net Using Deep Spatial Context Encoder and Nonstationary Joint Statistical Model for High-Resolution SAR Image Classification	Deep Spatial Context Encoder (DSCEN), Nonstationary Joint Statistical Model (NS-JSM), Feature Fusion Network (Fusion-Net)	-Integrates spatial and statistical features for improved classification accuracy. -The lightweight structure of DSCEN allows effective training with fewer samples. -NS-JSM captures inter-scale and intra-scale nonstationary correlation, enhancing feature compactness.	-The models used may be too simple to better model different types of image patches, potentially limiting performance	2023

3 Discussion

This paper has reviewed various feature extraction techniques for iris analysis, focusing on both traditional and deep learning-based approaches. A key observation from the related works is that deep learning methods, particularly Convolutional Neural Networks (CNNs), consistently outperform traditional approaches like Gabor filters and Histogram of Oriented Gradients (HOG) in terms of accuracy and robustness. CNN-based approaches excel in capturing intricate details such as lacunae, Wolfflin nodules, and contraction furrows, which are vital for effective iris recognition.

The reviewed works demonstrate that CNN architectures tailored for iris recognition achieve higher performance metrics, with accuracy rates typically exceeding 95% in controlled environments. These methods can adaptively learn relevant features directly from raw iris images, allowing them to detect minute details that might be overlooked by hand-crafted feature extraction techniques. For instance, studies employing variations of CNNs, such as U-Net and MobileNetV2, have shown significant improvements in segmentation accuracy, which is crucial for reliable iris feature extraction.

In contrast, traditional methods often struggle with the inherent variability in iris images caused by factors such as occlusions, illumination changes, and pupil dilation. Although techniques like Gabor filters are adept at capturing texture information, they are less effective in handling these variations, leading to reduced robustness in real-world scenarios.

In the context of evaluating image feature extraction methods, particularly in iris analysis, it is crucial to discuss the evaluation metrics used across the surveyed methods. Common evaluation metrics include accuracy, precision, recall, F1-score, and computational efficiency. Accuracy measures the proportion of correct predictions among the total predictions made, providing a straightforward assessment of a model's performance. Precision indicates the proportion of true positive results about the total predicted positives, while recall measures the model's ability to identify all relevant instances within the dataset. The F1-score is the harmonic mean of precision and recall, offering a balanced measure when dealing with class imbalances. Additionally, computational efficiency encompasses metrics such as training time, inference time, and resource utilization, which are essential for understanding the practical feasibility of deploying these models in real-world scenarios. Including a dedicated section on these evaluation metrics will provide a clearer framework for comparing the effectiveness of different methods and will help readers assess the strengths and weaknesses of each approach in a standardized manner.

The superiority of CNN-based approaches lies in their ability to automatically learn complex patterns and hierarchies from data. This advantage becomes especially important when dealing with the intricate structures present in the iris, where minute details play a pivotal role in identification. Moreover, deep learning methods can be fine-tuned with large-scale datasets, improving their generalizability and robustness across different environments. Another benefit is their ability to integrate multi-scale features, enabling the capture of both global and local patterns in iris images.

4 Conclusion

Most image feature extraction algorithms based on deep learning methods have demonstrated impressive results in the field of image processing, particularly in applications requiring high accuracy, such as medical imaging. The effectiveness of these algorithms often hinges on their ability to learn and extract relevant features directly from raw data, reducing the need for manual feature engineering. For medical imaging, where precision is critical, the performance of these algorithms must be optimized to ensure accurate diagnoses and assessments.

Deep learning-based methods have consistently outperformed traditional approaches, thanks to their capacity to handle complex and high-dimensional data. Techniques such as Convolutional Neural Networks (CNNs) and variations thereof have shown significant advancements in extracting minute details from images, such as those found in iris analysis. In our summary of deep learning-based methods, we highlighted their strengths, including their ability to adapt and improve with larger datasets and their robustness in various medical applications.

In the future directions, integrating multiple deep learning algorithms could further enhance accuracy in medical iris diagnosis and other related fields. By combining the strengths of different architectures, such as CNNs with Recurrent Neural Networks (RNNs), or employing ensemble methods, researchers can leverage complementary features and improve the overall performance of diagnostic systems. This future direction holds great promise for advancing medical imaging techniques and ensuring better outcomes in patient care and diagnosis.

References

[1] Ezhilarasan, M.," Image Enhancement for Iris Analysis Using Deep Learning Algorithms-A Brief Survey", In *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*, pp. 1-5, 2024, February. https://doi.org10.1109/icETITE58242.2024.10493485

[2] Poovayar Priya, M., and Ezhilarasan, M., "Iris segmentation technique using the iris-unet method", In *International Conference on Advanced Concepts for Intelligent Vision Systems*, pp. 235-249, 2023. https://doi.org/10.1007/978-3-031-45382-3_20

[3] Rafael C. Gonzalez, and Richard E. Wood, "Digital Image Processing", 3rd Edition, 2014.

[4] Priya, M.P. and Ezhilarasan, M., "A Hybrid Technique of Diagnosing Kidney Disorder Using Deep Neural Network", *International Journal of Online & Biomedical Engineering*, vol. 20, no. 15, 2024. https://doi.org/10.3991/ijoe.v20i15.50409

[5] Jensen B," Iridology simplified", California: Bernard Jensen, 1980.

[6] Mohan, P.P. and Murugesan, E., "A novel approach for detecting the presence of a lymphatic rosary in the iris using a 3-stage algorithm", *AIMS Bioengineering*, vol. *11*, no. 4, 2024. https://doi.org/10.3934/bioeng.2024023

[7] Zhou, W., Zhang, L., Gao, S. and Lou, X., "Gradient-based feature extraction from raw bayer pattern images", *IEEE Transactions on Image Processing*, vol. *30*, pp.5122-5137, 2021. https://doi.org/10.1109/TIP.2021.3067166

[8] Liang, W., Wu, Y., Li, M., Zhang, P., Cao, Y. and Hu, X., "A Feature Fusion-Net Using Deep Spatial Context Encoder and Nonstationary Joint Statistical Model for High-Resolution SAR Image Classification", 2021. https://doi.org/10.1109/TGRS.2020.3042274

[9] Nie, L., Lin, C., Liao, K., Liu, S. and Zhao, Y., "Unsupervised deep image stitching: Reconstructing stitched features to images", *IEEE Transactions on Image Processing*, vol. *30*, pp.6184-6197, 2021. https://doi.org/10.1109/TIP.2021.3092733

[10] Sun, G., Fu, H., Ren, J., Zhang, A., Zabalza, J., Jia, X. and Zhao, H., "SpaSSA: Superpixelwise adaptive SSA for unsupervised spatial-spectral feature extraction in the hyperspectral image", *IEEE Transactions on Cybernetics*, 2021. https://doi.org/10.1109/TCYB.2021.3104100

[11] Zhang, M., Gong, M., He, H. and Zhu, S., "Symmetric all convolutional neural-network-based unsupervised feature extraction for hyperspectral images classification", *IEEE Transactions on Cybernetics*, 2020. https://doi.org/10.1109/TCYB.2020.3020540

[12] Yu, W., Zhang, M. and Shen, Y., "Spatial revising variational autoencoder-based feature extraction method for hyperspectral images", *IEEE Transactions on Geoscience and Remote Sensing*, vol. *59*, No. 2, pp.1410-1423, 2020. https://doi.org/10.1109/TGRS.2020.2993141

[13] Tu, B., Zhou, C., Liao, X., Li, Q. and Peng, Y., "Feature extraction via 3-D block characteristics sharing for hyperspectral image

classification", *IEEE Transactions on Geoscience and Remote Sensing*, vol. *59*, No. 12, pp.10503-10518, 2020. https://doi.org/10.1109/TGRS.2020.3042274

[14] Wang, S., Ding, C., Zhang, N., Liu, X., Zhou, A., Cao, J. and Shen, X., "A cloud-guided feature extraction approach for image retrieval in mobile edge computing", *IEEE Transactions on Mobile Computing*, vol. *20*, No. 2, pp.292-305, 2019. https://doi.org/10.1109/TMC.2019.2960939

[15] Ge, L., Wei, X., Hao, Y., Luo, J. and Xu, Y., "Unsupervised Histological Image Registration Using Structural Feature Guided Convolutional Neural Network", IEEE *Transactions on Medical Imaging*, 2022. https://doi.org/10.1109/TMI.2021.3118464

[16] Jing, M. and Zhang, G., Attributed scattering center extraction with genetic algorithm. *IEEE Transactions on Antennas and Propagation*, vol. *69*, No. 5, pp. 2810-2819, 2020. https://doi.org/10.1109/TAP.2020.3027630

[17] Sun, Q. and Ge, Z., "Gated stacked target-related autoencoder: A novel deep feature extraction and layerwise ensemble method for industrial soft sensor application", *IEEE Transactions on Cybernetics*, 2022. https://doi.org/10.1109/TCYB.2021.3087993

[18] Li, D., Kong, F., Liu, J. and Wang, Q., "Superpixel-Based Multiple Statistical Feature Extraction Method for Classification of Hyperspectral Images", *IEEE Transactions on Geoscience and Remote Sensing*, vol. *59*, No. 10, pp.8738-8753, 2021. https://doi.org/10.1109/TGRS.2020.3031726

[19] Zhang, X., Jiang, X., Jiang, J., Zhang, Y., Liu, X. and Cai, Z., "Spectral–spatial and superpixelwise PCA for unsupervised feature extraction of hyperspectral imagery", *IEEETransactions on Geoscience and Remote Sensing*, *60*, pp.1-10, 2021. https://doi.org/10.1109/TGRS.2021.3067167

[20] Nagamura, Y., Arima, K., Arai, M. and Fukumoto, S., "Layout Feature Extraction Using CNN Classification in Root Cause Analysis of LSI Defects", *IEEE Transactions on Semiconductor Manufacturing*, vol. *34*, No. 2, pp.153-160, 2021. https://doi.org/10.1109/TSM.2021.3067168

[21] Xiong, Y.," Development of an AI-Driven Model for Drug Sales Prediction Using Enhanced Golden Eagle Optimization and XGBoost Algorithm", *Informatica*, vol. *49*, no. 17, 2025. https://doi.org/10.31449/inf.v49i17.7491

[22] El Houby, E.M., "A Review of Machine Learning Techniques in the Medical Domain", *Informatica*, vol. *49*, no. 16, 2025. https://doi.org/10.31449/inf.v49i16.6934

[23] Xie, J., Li, Z., Zhou, Z. and Liu, S., "A novel bearing fault classification method based on XGBoost: The fusion of deep learning-based features and empirical features", *IEEE Transactions on Instrumentation and Measurement*, vol. *70*, pp.1-9, 2020. https:/doi.org/10.1109/TIM.2020.3042275