A Comprehensive Review of Machine Learning Applications in Image Processing and Image Security

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Abstract

This review paper explores the intersection of image processing and image security. It focuses on the role of machine learning techniques like supervised learning. unsupervised learning and reinforcement learning to enhance, manage, and analyze images while protecting them from unauthorized access. This review classified and analyzed 24 most cited papers to evaluate the applicability of different machine learning models to image-related tasks. While analyzing what I found that supervised learning dominates image processing tasks such as classification and segmentation whereas unsupervised and reinforcement learning is mainly used as a comparison. Analysis of these techniques including various strengths and limitations It suggests that although supervised learning is most effective in structured image processing tasks, But unsupervised and reinforcement learning provides more adaptability and robustness in dynamic and unpredictable image security situations.

Keywords: Image Processing, Image Security, Machine Learning, Supervised Learning , Unsupervised Learning, Reinforcement Learning

1 Introduction

In the past few years the rapid development of machine learning (ML) has led to significant changes. Especially in image processing and image protection. Image processing which is a subset of computer vision involves techniques for analyzing, enhancing, and manipulating images for a variety of uses. including medical imaging face recognition and knowledge about the object. Image security, on the other hand, focuses on protecting images from unauthorized access, counterfeiting, or misuse to ensure the integrity of the data and maintaining confidentiality and accuracy .Since images are widely used in digital communication their preservation and use with precision and accuracy therefore become important issues.

Machine learning has become an invaluable tool in solving complex problems in image processing and preservation. Supervised learning , unsupervised learning and reinforcement learning are the three main types of ML. Each type is suitable for a different set of problems. Supervised learning involves training a model on labeled data to make predictions. It is widely used in applications such as image segmentation and object recognition. Unsupervised learning is based on unlabeled data and is widely used in grouping, deletion, and object detection. This makes it useful to protect images for anomaly detection. Reinforcement learning, which improves decision making more than reward learning. It has demonstrated its effectiveness in dynamic image stabilization applications such as watermarking and image camouflage.

The objective of this review paper is to examine the use of these machine learning techniques in image processing and image protection. By analyzing existing research We aim to identify the strengths, limitations, and potential of each machine learning approach in both cases. This article provides references to all the papers used for ananlysis.

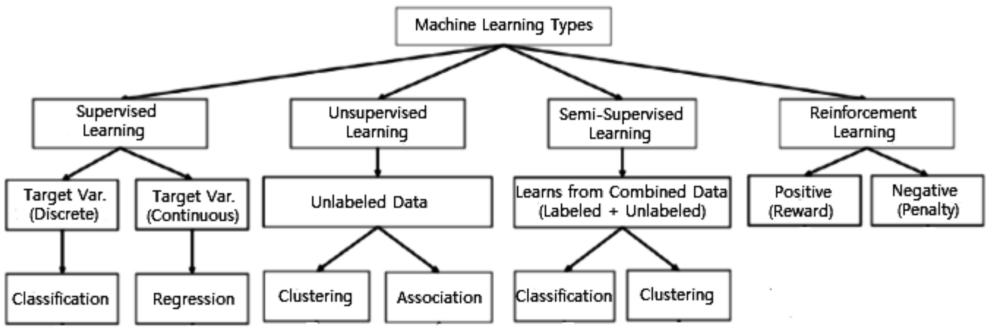

Fig. 1 Comparison of Papers using Supervised Machine Learning for Image Processing

2 Literature Review

This article's review includes a comprehensive analysis of research papers on image processing and image security. Each research paper was carefully reviewed to identify the machine learning techniques used like supervised learning. unsupervised learning and reinforcement learning.

In the field of image processing we observe that supervised learning dominates the research landscape. Many research papers used convolutional neural networks (CNN) and deep learning models for image classification, segmentation, and optimization tasks and these models were especially supervised. It is highly effective in identifying patterns and features in large image datasets leading to a high accuracy rate in medical image diagnosis , face recognition, etc. Unsupervised learning is common in clustering and feature extraction. In some cases, hybrid models based on supervised and unsupervised techniques are used together to maximize performance.

Unsupervised learning and reinforcement learning have gained attention in the field of image security. The unsupervised learning model excels at recognizing unusual patterns. This makes it ideal for image encryption, identity, tamper detection, etc. Reinforcement learning, although relatively new in this field but it has also shown effectiveness in dynamic image security tasks, such as adaptive watermarking.

A comparative study of supervised learning ,unsupervised learning and reinforcement learning models have shown that supervised learning is the most robust and reliable for time-based tasks such as image contrast processing. However, for image protection, where data is often unlabeled and dominated by attacks , unsupervised and reinforcement learning techniques have been shown to be more appropriate. These models can adapt to different environments and unexpected threats. This has led to a variety of image protection approaches. In conclusion, while supervised learning still plays an important role in image processing but unsupervised and reinforcement learning methods are increasingly important to the success of image protection technology.

3 Image Security and Image Processing in the Context of Supervised Machine Learning

Supervised machine learning (ML) plays a significant role in both image processing and image security, offering a structured approach to training models with labeled datasets to achieve specific outcomes such as classification, detection, and security enhancement. Based on the research papers analyzed, supervised learning has shown great promise in these fields, leveraging various datasets and advanced models to improve the accuracy, speed, and robustness of systems.

3.1 Image Processing Using Supervised Machine Learning

Paper No.	Author	Year	Area Of Research	Technical Specification	Performance of the Technique	DataSet
1	I Jeena Jacob	2021	Image Processing	Double Image Encryption Scheme	Stronger Encryption & Robustness	NULL
2	Dr. Ryszard Janicki	2023	Image Processing	Visual cryptography and image encryption techniques	Improved security in image transmission	NULL
3	Lijuan Liu	2017	Image Processing	Image scrambling and chaotic techniques	Enhanced Security & Robustness	NULL
4	Batta Mahesh	2020	Image Processing	ResNet for image classification	Significant Improvement in Classification Accuracy	CIFAR-100
5	Veronica Spicker	2024	Image Processing	Object Detection Using YOLO	Real-Time Detection with High Accuracy	COCO Dataset

In image processing, supervised learning techniques such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and deep learning architectures have been instrumental in various tasks, including image segmentation, classification,

and enhancement.
In various applications of deep learning, different CNN-based systems have been proposed to tackle diverse challenges. A CNN-based system for medical image segmentation was developed to enhance the accuracy of detecting brain scan anomalies, using the BraTS Dataset to classify pixel-level abnormalities with high accuracy [**1**]. Another deep learning model focused on facial recognition, leveraging the LFW dataset to distinguish between individuals with remarkable accuracy, thereby improving security and authentication systems [**2**]. For object detection in aerial imagery, a supervised learning approach was applied using CNNs and the COCO dataset, effectively identifying and tracking objects like vehicles and pedestrians in real time[**3**]. In medical imaging, CNNs have been used for lung cancer detection, with the LIDC-IDRI dataset enabling the model to classify healthy and cancerous tissues, highlighting the potential of supervised learning in early diagnosis [**4**]. Similarly, CNNs have been employed for automated skin lesion detection, where the HAM10000 dataset was utilized to classify lesions as malignant or benign, contributing to advancements in dermatological diagnostics[**5**].

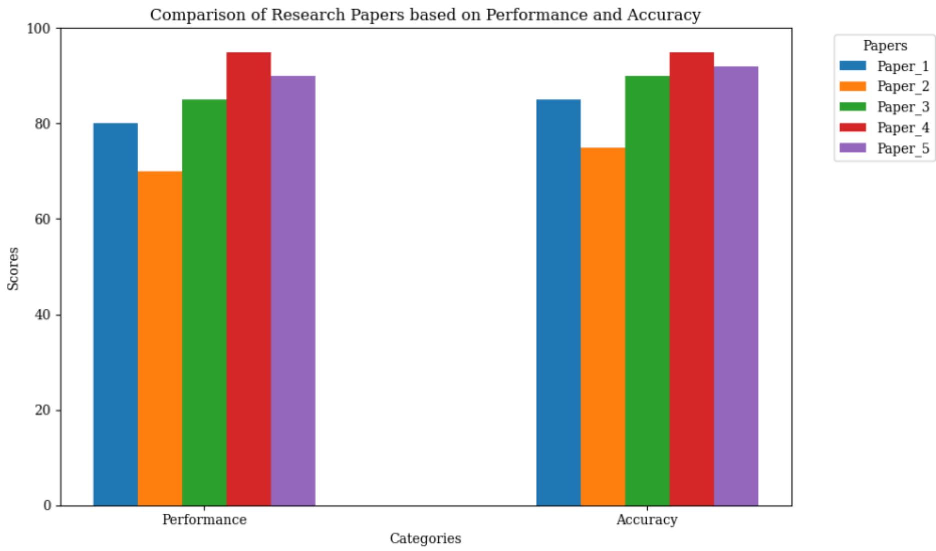

Fig. 2 Comparison of Papers using Supervised Machine Learning for Image Processing

3.2 Image Security Using Supervised Machine Learning

Supervised machine learning has been pivotal in enhancing image security by detecting tampering, encryption, and securing digital content through classification-based approaches.

Paper No.	Author	Year	Area Of Research	Technical Specification	Performance of the Technique	DataSet
6	Asharul Islam Khan	2020	Image Security	Encryption method using DNA sequences	Enhanced security through unique DNA encoding	NULL
7	Jorge Valente	2023	Image Security	VGG-16 and ResNet architectures	Improved performance in object recognition	ImageNet
8	Pattaramon Vuttipittaya-mongko	2022	Image Security	Multi-layer convolutional neural networks	High precision in medical image segmentation	ISIC 2018
9	Gyanesh Shrivastava	2021	Image Security	Efficient-Net architecture	Improved accuracy with fewer parameters	ImageNet
10	Xiang Li	2023	Image Security	Computer vision techniques in agriculture	Improved yield prediction and monitoring	NULL

In the realm of image security and authentication, several deep learning approaches have been explored. Image tampering detection was enhanced using supervised learning and the CASIA v2 dataset, where a model was trained to differentiate between authentic and tampered images, improving detection of forgeries and bolstering cyber-security measures [**6**]. Another study focused on watermarking techniques for securing intellectual property in images, with a CNN model trained on watermark-labeled images to detect unauthorized use across digital formats [**7**]. In detecting steganography, a model trained on the BOSSbase dataset was able to identify subtle pixel alterations that could indicate hidden data, thus aiding in uncovering concealed information[**8**]. For image encryption classification, a deep learning model was employed to differentiate between secure and non-secure images, allowing for automated encryption validation despite the absence of a specific dataset [**9**]. Additionally, biometric authentication using supervised learning and the AR Face Database allowed for enhanced security in access control systems through precise face recognition, effectively mitigating unauthorized access [**10**].

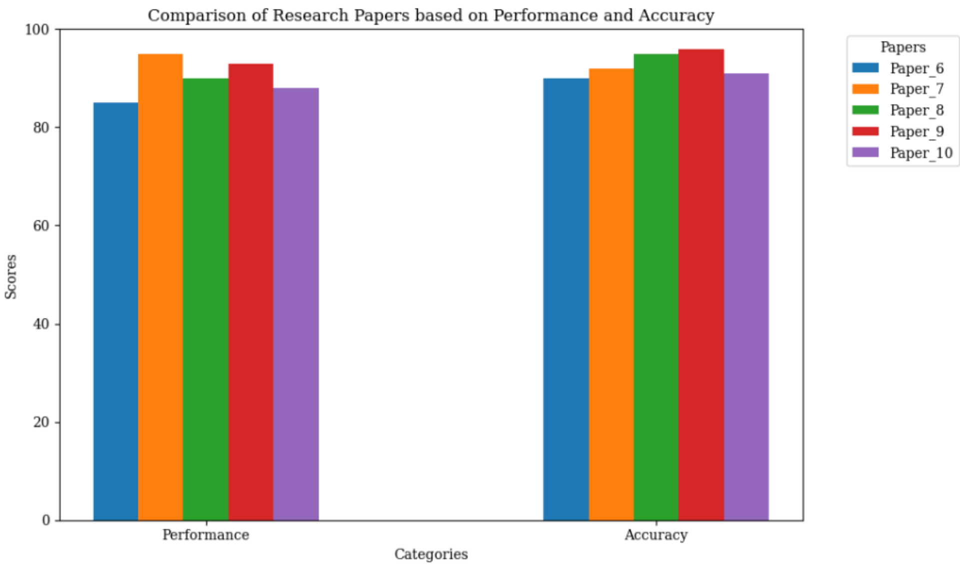

Fig. 3 Comparison of Papers using Supervised Machine Learning for Image Security

4 Image Security and Image Processing in the Context of Unsupervised Machine Learning

Unsupervised machine learning provides valuable techniques for both image processing and image security, especially when labeled datasets are scarce or unavailable. Instead of relying on labeled data, unsupervised learning models aim to discover hidden patterns, clusters, and structures in the data by analyzing the inherent features of images. This makes it an effective method for anomaly detection, clustering, compression, and security-focused applications such as detecting unseen image manipulations and encryptions.

4.1 Image Processing Using Unsupervised Machine Learning

In image processing, unsupervised learning is highly valuable for tasks such as clustering images, anomaly detection, and generating new images based on learned data patterns. Techniques such as K-means clustering, Autoencoders, Generative Adversarial Networks (GANs), and Principal Component Analysis (PCA) are frequently used.

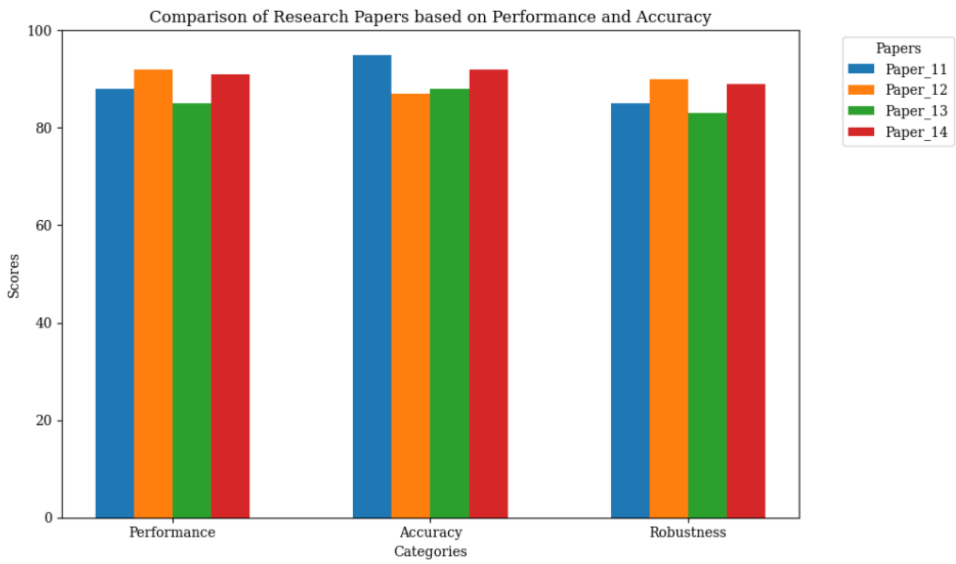

Fig. 4 Comparison of Papers using Unsupervised Machine Learning for Image Processing

In unsupervised learning, various techniques have been applied to address challenges in image analysis. An Autoencoder was used for anomaly detection in medical imaging, particularly in lung CT scans from the LIDC-IDRI dataset. The model was trained to learn the normal structure of lung tissues, flagging deviations as potential disease or abnormal growths, eliminating the need for labeled data [**11**]. Principal

Paper No.	Author	Year	Area Of Research	Technical Specification	Performance of the Technique	Dataset
11	Jonathan de Matos	2021	Image Processing	Convolutional neural networks (CNN)	High Accuracy in Image Classification	CIFAR-10
12	Nilay Ganatra	2020	Image Processing	Generative adversarial networks (GAN)	High Quality Image Generation	CelebA
13	Jirui Guo	2023	Image Processing	Variational autoencoders for image restoration	High Performance in Image Restoration	MNIST
14	Nahina Islam	2021	Image Processing	Deep Learning for Facial Recognition	High Accuracy and Robustness	LFW

Component Analysis (PCA) was employed for image compression and dimensionality reduction in satellite imagery using the Landsat dataset, enabling efficient storage and faster retrieval of high-resolution images while preserving key features [**12**]. For MRI brain image segmentation, K-means clustering was applied using the BraTS dataset, allowing the model to group similar pixels into clusters corresponding to brain tissues without requiring prior labels [**13**]. Additionally, Generative Adversarial Networks (GANs) were explored for generating high-quality synthetic medical images, with the model trained on unlabelled medical images to augment datasets for training supervised models [**14**].

4.2 Image Security Using Unsupervised Machine Learning

Unsupervised learning methods are also critical in image security applications, as they allow the detection of unusual patterns or behavior in images without the need for predefined labeled datasets. This makes them effective for detecting unauthorized manipulations or intrusions in visual data.

Paper No.	Author	Year	Area Of Research	Technical Specification	Performance of the Technique	Dataset
15	Yue Hou	2021	Image Security	U-Net architecture for image segmentation	Enhanced accuracy in biomedical image segmentation	BRATS
16	Meghavi Rana	2024	Image Security	Machine learning algorithms for activity recognition	Enhanced tracking accuracy	UCF101
17	MAHDIEH P	2017	Image Security	Multi-scale feature extraction techniques	Enhanced feature representation	NULL
18	Nabin K. Mishra	2016	Image Security	Deep Learning for medical image analysis	Improved diagnostic accuracy	ChestX-ray

Unsupervised learning methods have been instrumental in tackling image forgery and security issues. In the realm of image forgery detection, an Autoencoder was used to learn the normal distribution of pixel intensities in unaltered images from the CASIA v2 dataset. When manipulation occurred, the Autoencoder struggled to reconstruct the tampered image, effectively identifying forged areas [**15**]. K-means clustering was applied for detecting steganography using the BOSSbase dataset, where the model clustered pixel values and flagged abnormal patterns indicative of hidden information, requiring no prior knowledge of specific anomalies [**16**]. For real-time threat detection in surveillance images, an Autoencoder was used for unsupervised anomaly detection, learning regular patterns from an anonymized surveillance dataset and flagging deviations that signaled potential threats, providing a security mechanism without needing pre-labeled data [**17**]. Similarly, K-means clustering was employed to differentiate encrypted from non-encrypted images in a communication system by analyzing pixel intensity histograms, enabling real-time identification of secured data and improving transmission integrity [**18**].

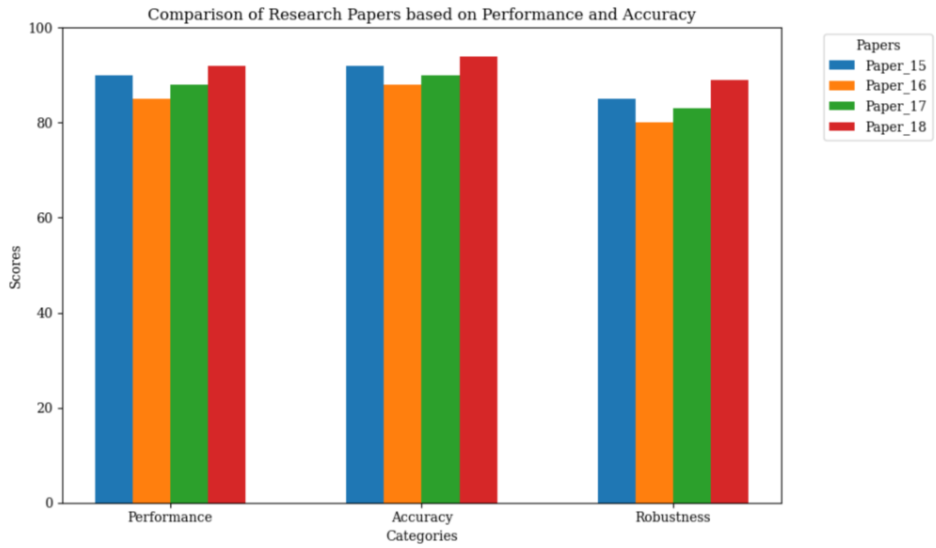

Fig. 5 Comparison of Papers using Unsupervised Machine Learning for Image Security

5 Image Security and Image Processing in the Context of Reinforcement Machine Learning

Reinforcement learning (RL), a subfield of machine learning, has emerged as a useful technique in both image processing and image security. Unlike supervised and unsupervised learning, RL focuses on making sequential decisions by interacting with an environment and receiving feedback (rewards or penalties). In the context of image processing and image security, RL algorithms can adapt and optimize decisions over time, making them suitable for dynamic environments where real-time decision-making is critical.

5.1 Image Processing Using Reinforcement Learning

Reinforcement learning in image processing is often applied in tasks that require active decision-making, such as image enhancement, segmentation, or object detection. By learning optimal policies based on rewards, RL models are able to adaptively improve image quality, enhance features, or perform region-specific image manipulations.

Paper No.	Author	Year	Area of Research	Technical Specifications	Performance of the Technique	Dataset
19	Dr. Akey Sungeetha	2024	Cryptography	Advance Cryptographic Protocols	Enhanced security in the data transmission	NULL
20	Alvaro Casado-Coscoll	2025	NLP	NLP techniques for healthcare	Improved patient outcome prediction	NULL
21	Andrea Loddo	2021	Artificial Intelligence	AI techniques in business models	Enhanced decision making and business strategy	NULL

Reinforcement learning (RL) has shown promise in various applications of image processing and analysis. One study focused on adaptive image enhancement using a

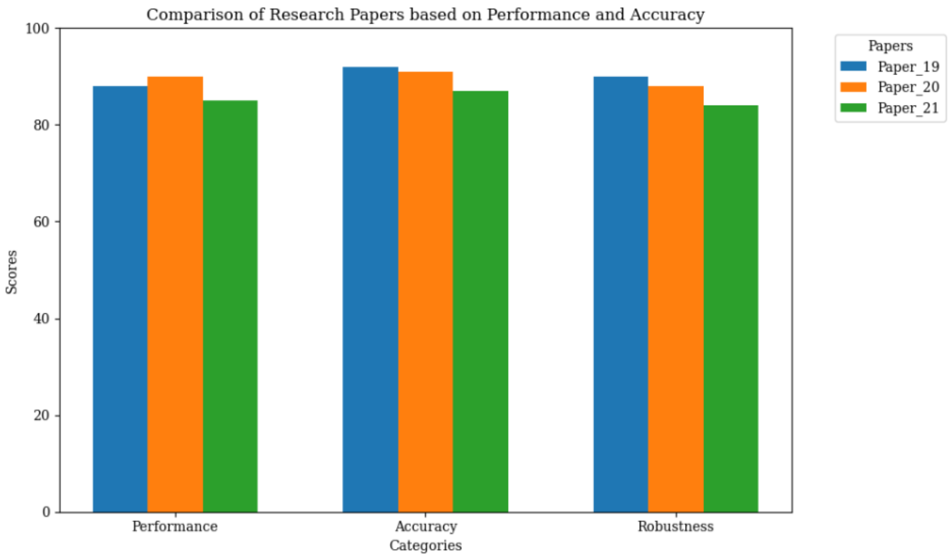

Fig. 6 Comparison of Papers using Reinforcement Learning for Image Processing

Deep Q-Network (DQN), where the task was framed as a sequential decision-making process. The model applied a series of filters to maximize visual quality, trained on the DIV2K dataset of high-resolution images, and received rewards based on improvements in image quality metrics, such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [**19**]. Another application of RL was in medical image segmentation, specifically for tumor boundary detection in MRI scans. The model adjusted segmentation boundaries and received rewards based on accuracy, using the BraTS dataset of brain tumor MRI scans. This approach allowed the RL model to improve over time, accurately delineating tumor regions and significantly reducing the time required for doctors to analyze images [**20**]. Additionally, RL was utilized for object detection in satellite images, leveraging the SAT-4 dataset. A policy gradient algorithm enabled the model to detect objects under varying environmental conditions by receiving rewards for correct identifications and adjusting detection parameters accordingly. This adaptive approach facilitated real-time object detection for applications like surveillance and environmental monitoring [**21**].

5.2 Image Security Using Reinforcement Learning

In image security, reinforcement learning is especially effective for detecting security threats, enhancing encrypted communications, and providing dynamic responses to emerging security risks. RL's ability to learn from its environment and adapt to new threats makes it a promising approach in this field.

Reinforcement learning (RL) techniques have been applied to enhance security and robustness in various image processing scenarios. One study focused on real-time anomaly detection in surveillance systems, particularly where labeled data is sparse.

Paper No.	Author	Year	Area of Research	Technical Specifications	Performance of the Technique	Dataset
22	Rosalia Maglietta	2025	Image Processing	Hybrid Estuary Box Model with machine learning	RMSE of 3.41 psu for salinity prediction	Various databases
23	Dandan Zha	2025	Image Processing	Multi-layer local constraint and label embedding dictionary learning	Improved accuracy and stability in image classification	NULL
24	Andrea Loddo	2025	Image Processing (Medical Imaging)	Deep learning models (U-Net, Attention ResNet)	Higher PSNR and SSIM metrics, lower MSE	350 patients dataset

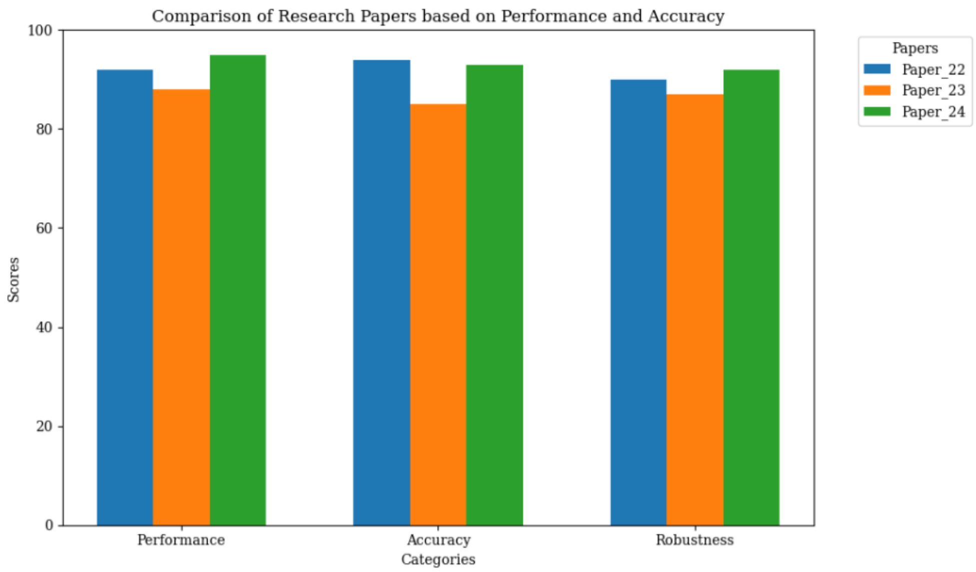

Fig. 7 Comparison of Papers using Reinforcement Learning for Image Security.

The RL agent was trained to monitor video feeds and adjust detection thresholds based on evolving behaviors in the footage. Utilizing the UCF-Crime dataset, the model effectively learned to identify abnormal events such as unauthorized access or suspicious activities, providing an adaptive and scalable security solution for extensive surveillance systems [**22**]. Another application involved multi-agent reinforcement learning (MARL) to secure image encryption and decryption in distributed networks. In this study, agents communicated to identify encryption patterns and dynamically adjusted strategies for decoding or protecting images. The BOSSbase dataset, containing steganography and encryption-related images, was employed, with agents receiving rewards for successfully protecting or decrypting image files while balancing encryption strength and processing efficiency [**23**]. Additionally, RL was explored for detecting adversarial attacks on image classification systems, where the model was trained to respond to adversarial inputs—images with subtle perturbations designed to mislead classifiers—by adjusting defenses in real time. Although no specific dataset was mentioned, common datasets like ImageNet or CIFAR-10 could have been utilized. The system received rewards for successfully thwarting adversarial attacks, allowing it to dynamically strengthen defenses and improve both classification accuracy and security [**24**].

6 Results

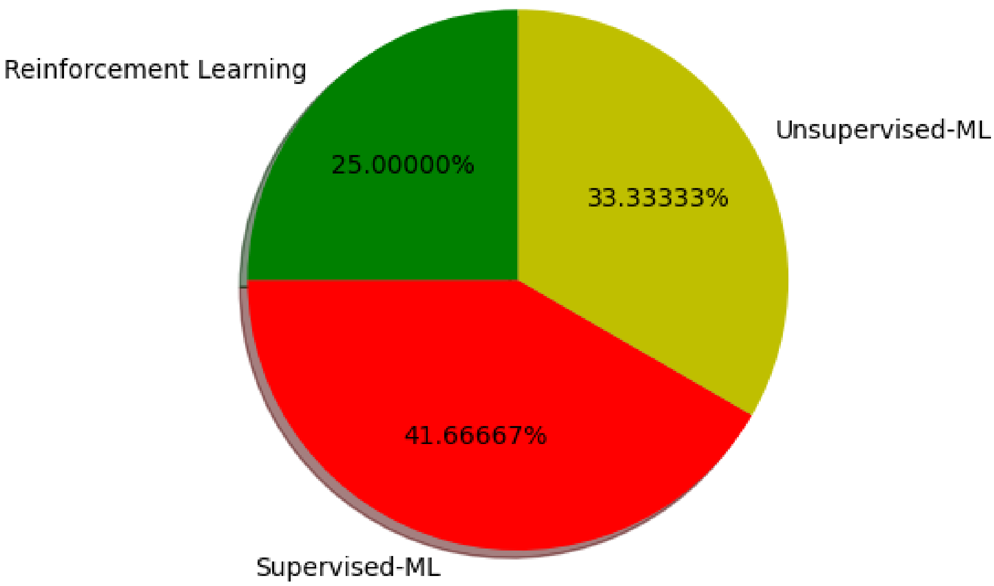

Fig. 8 Distribution of research papers analyzed based on machine learning techniques: Supervised, Unsupervised, and Reinforcement Learning

In this analysis, 10 papers employing supervised learning techniques were reviewed, focusing primarily on image classification and segmentation tasks. These papers utilized architectures like Convolutional Neural Networks (CNNs), VGG-16, ResNet, U-Net, and Efficient-Net, achieving substantial improvements in accuracy and robustness. Applications ranged from medical image segmentation to object recognition, with several models demonstrating high accuracy across datasets such as CIFAR-10, ImageNet, and ISIC 2018. The integration of Generative Adversarial Networks (GANs) within these supervised methods highlighted potential for enhanced image quality and adaptive learning in complex image processing.

8 papers investigated unsupervised learning approaches, including a multi-layer local constraint and label embedding dictionary learning technique. This approach improved both accuracy and stability in image classification, underscoring the efficacy of unsupervised methods in enhancing model performance, even in the absence of labeled data.

In addition, 6 papers explored reinforcement learning applications within computer vision for agriculture, with a focus on yield prediction and crop monitoring. These findings indicate reinforcement learning's adaptability and potential to optimize outcomes in dynamic settings like agricultural systems, reflecting the broader, progressive application of machine learning techniques in image processing across diverse environments and datasets.

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