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RESEARCHING THE POSSIBILITIES OF USING AI TECHNOLOGIES FOR DIGITAL IMAGE PROCESSING: REVIEW AND APPLICATIONS

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Анотація. У статті досліджуються можливості використання технологій штучного інтелекту (ШІ) у сфері обробки цифрових зображень, аналізуються поточні застосування та майбутні перспективи. Техніки обробки зображень на основі ШІ, такі як зниження шуму, суперроздільна здатність, генерація зображень, трансформують традиційні підходи, забезпечуючи новий рівень точності, ефективності та творчого потенціалу. У статті розглядаються застосування ШІ в різних галузях, зокрема в охороні здоров’я для медичної діагностики, у сфері культури для реставрації мистецтва, в промисловості для контролю якості та в маркетингу для створення контенту.
Ключові слова: обробка цифрових зображень, штучний інтелект, генерація зображень, медична діагностика
Abstract. This paper explores the potential of artificial intelligence (AI) technologies in the field of digital image processing, analyzing current applications and future prospects. AI-based image processing techniques, such as noise reduction, super-resolution, inpainting, and image generation, are transforming traditional approaches, offering new levels of accuracy, efficiency, and creative potential. The paper examines AI applications across various fields, including healthcare for medical diagnostics, cultural heritage for art restoration, industry for quality control, and marketing for content creation.
Keywords: digital image processing, artificial intelligence, image generation, medical diagnostics.

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INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques to it.

Image processing usually refers to digital image processing, but optical and analog image processing also are possible. In electrical engineering and computer science, analog image processing is any image processing task conducted on two-dimensional analog signals by analog means as opposed to digital image processing. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the buildup of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more), digital image processing may be modeled in the form of multidimensional systems [1].

Image analysis is the extraction of meaningful information from images, mainly from digital images by means of digital image processing techniques. Image analysis tasks can be as simple as reading bar coded tags or as sophisticated as identifying a person based on faces. There are many different techniques used in automatically analyzing images. Each technique may be useful for a small range of tasks; however, there are still no known methods of image analysis that are generic enough for wide ranges of tasks, compared with the abilities of a human's image-analyzing capabilities. Examples of image analysis techniques in different fields include: 2D and 3D object recognition, image segmentation, motion detection (e.g., single particle tracking), video tracking, optical flow, medical scan analysis, 3D pose estimation, automatic number plate recognition, and so on [2,3].

Digital image analysis is the process in which a computer or electrical device automatically studies an image to obtain useful information from it. Note that the device is often a computer, but it may also be an electrical circuit, a digital camera, or a mobile phone. The applications of digital image analysis are continuously expanding through all areas of science and industry, including medicine, such as detecting cancer in an MRI scan; microscopy, such as counting the germs in a swab; remote sensing, such as detecting intruders in a house and producing land cover/land use maps; astronomy, such as calculating the size of a planet; materials science, such as determining if a metal weld has cracks; machine vision, such as automatically counting items in a factory conveyor belt; security, such as detecting a person's eye color or hair color; robotics, such as avoiding steering into an obstacle; optical character recognition, such as detecting automatic license plate; assay microplate reading, such as detecting where a chemical was manufactured; and metallography, such as determining the mineral content of a rock sample [4].

Computers are indispensable for the analysis of large amounts of data, for tasks that require complex computation, or for the extraction of quantitative information. *Computer image analysis* largely involves the fields of computer or machine vision, and medical imaging, and makes heavy use of pattern recognition, digital geometry, and signal processing. It is the quantitative or qualitative characterization of 2D or 3D digital images. Two-dimensional images are usually analyzed in computer vision, whereas 3D images in are analyzed in medical imaging. On the other hand, the human visual cortex is an excellent image analysis apparatus, especially for extracting higher level information, and for many applications—including medicine, security, and remote sensing—human analysts still cannot be replaced by computers. For this reason, many important image analysis tools such as edge detectors and neural networks are inspired by human visual perception models [2,5].

In fact, we can view the process of information extracting from stego images as a special kind of digital image analysis, since its input is an image and its output is the secret information or the conclusion whether the stego image is authentic or watermarked [6]. Thus, the topic of information hiding in images is closely related to digital image processing and analysis, and many traditional image processing and analysis techniques can be used in information hiding [3-6].

Artificial intelligence (AI) opens new possibilities for working with images, allowing to automate and improve processes such as recognition, analysis, quality improvement and even image generation. In particular, technologies based on machine learning and deep neural networks, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), have greatly expanded the capabilities of image processing.

1. AN OVERVIEW OF AI TECHNOLOGIES FOR IMAGE PROCESSING

1.1. Machine learning and deep learning

Machine learning and deep learning have brought transformative advancements to image processing by enabling detailed analysis, enhancement, and generation of images. The key technologies driving these capabilities include Convolutional Neural Networks (CNNs) [7-10], Recurrent Neural Networks (RNNs) [11], and Generative Adversarial Networks (GANs) [12].

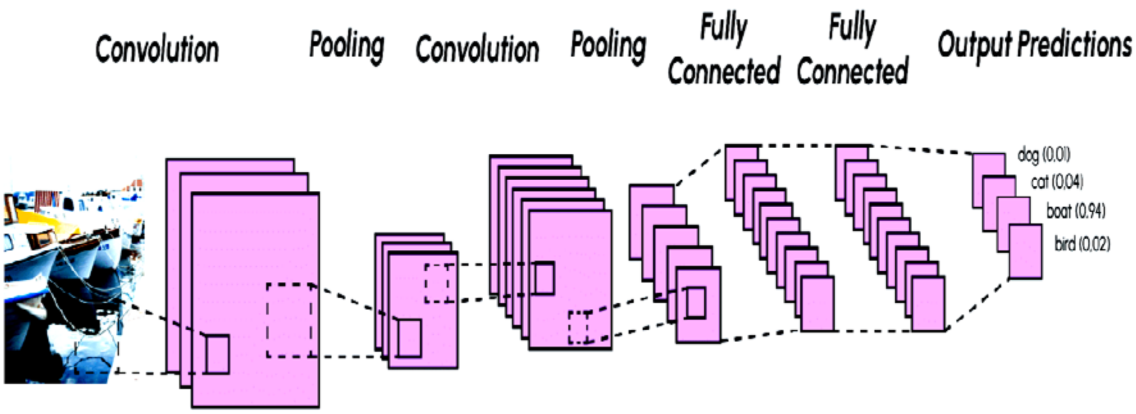

Figure 1 – An example of CNNs using

Convolutional Neural Networks (CNNs)

CNNs are specially designed to handle grid-like data structures, such as images. They use layers of filters that "convolve" or slide across an image, identifying features like edges, textures, and eventually entire objects. CNNs are widely used for tasks like image classification, object detection, and facial recognition, as they capture both simple and complex features effectively [7]. The main components of a CNN are convolutional layers, which apply filters to capture local features in images; pooling layers, which reduce the spatial size of feature maps, improving efficiency; fully connected layers, which combine and classify features extracted by previous layers [8,9].

Recurrent Neural Networks (RNNs)

RNNs are typically applied to sequential data, such as language or time series, they are also valuable in image-related tasks that involve sequences, like video processing or generating image captions. RNNs can be paired with CNNs to create descriptions of images or analyze video frames sequentially. Variants like Long Short-Term Memory (LSTM) networks help retain essential information across longer sequences, which is useful when processing time-dependent image data [11].

Generative Adversarial Networks (GANs)

GANs consist of two competing networks: a generator and a discriminator. The generator creates synthetic images, while the discriminator attempts to distinguish real images from those generated. This adversarial training process enables GANs to produce highly realistic images. GANs are transformative for tasks like image synthesis, style transfer, and restoration. Examples of popular GAN types include StyleGAN, that used to generate high-quality images of faces or objects with specific styles and Pix2Pix and CycleGAN, which enable image-to-image translation, such as converting black-and-white images to color [12].

1.2. Tools and libraries

There are several powerful libraries and tools widely used for image processing tasks in machine learning and deep learning. These libraries, such as *TensorFlow* [13], *PyTorch* [14], and *OpenCV* [15], offer various functionalities that simplify working with images, from preprocessing and data augmentation to building complex neural network architectures for analysis, enhancement, and generation.

TensorFlow is an open-source deep learning framework developed by Google that is highly flexible and supports both high- and low-level programming for building neural networks. It has robust tools for image processing, including *TensorFlow Hub*, where users can access pre-trained models for tasks such as image classification, object detection, and segmentation*; tf.image module*, which provides efficient tools for common image preprocessing operations like resizing, cropping, rotating, and color adjustments.; *Keras API*, a high-level neural network library built into TensorFlow, simplifies building and training complex neural networks for image processing [16]. With Keras, users can construct models such as CNNs and GANs using a straightforward syntax, making it easier for beginners and experienced developers alike.

PyTorch, developed by Facebook's AI Research lab, is another popular deep learning framework that is highly appreciated for its intuitive and flexible approach, especially among researchers. PyTorch is well-suited for complex image processing tasks due to its dynamic computation graph and strong support for customizations such *torchvision* [17], an extensive library in PyTorch designed for image processing, includes pre-trained models (e.g., ResNet, VGG) and utilities for image datasets. It provides essential functions for image transformations, augmentations, and loading datasets, making it easier to prepare data for neural network training. *Autograd* in PyTorch allows for automatic differentiation, which is essential for backpropagation in deep learning. This feature is especially useful for experimentation and debugging when working with complex image processing tasks like GAN training [18].

OpenCV is a powerful, open-source computer vision library that provides a large set of tools specifically tailored for image and video processing. It's widely used in applications that require efficient image manipulation and analysis. OpenCV provides a wide range of functions for image manipulation, such as filtering, edge detection, color conversion, and geometric transformations (e.g., rotation, scaling). This makes it a go-to tool for preparing images for training or analysis [14-17]. *OpenCV* includes algorithms like Haar Cascades and Histogram of Oriented Gradients (HOG), which are useful for detecting faces, eyes, and other objects in images. These algorithms are efficient and can run in real-time, making OpenCV a good choice for live video processing.

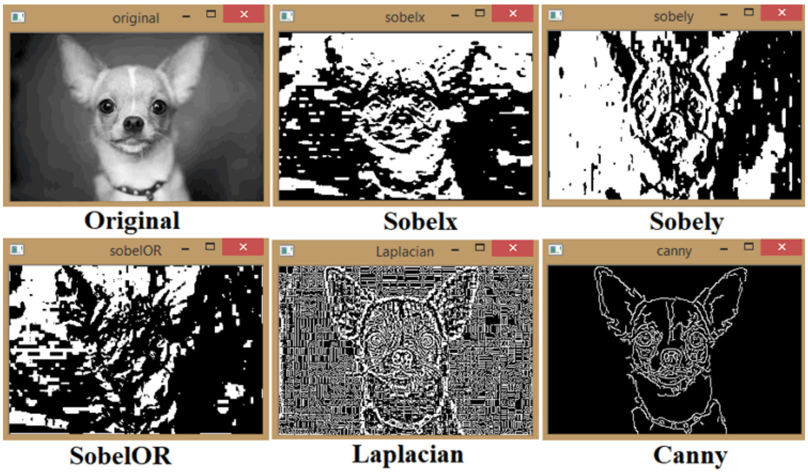

Figure 2 – Image manipulation in Python OpenCV

Each of these libraries plays a critical role in image processing workflows. TensorFlow and PyTorch are preferred for building and training deep learning models, offering extensive support for image preprocessing and ready-to-use neural network architectures. OpenCV, on the other hand, is a versatile tool for classic image processing techniques and real-time image manipulation, and it integrates well with machine learning frameworks. Together, these libraries provide a comprehensive toolkit for developers and researchers working on image processing applications across various domains [21-25].

2. OBJECT RECOGNITION AND IMAGE CLASSIFICATION

2.1. Object recognition algorithms

Object recognition algorithms are fundamental in computer vision, enabling machines to identify and locate specific objects within an image. Convolutional neural networks (cnns) have become the core technology for object recognition tasks due to their ability to capture complex spatial hierarchies and patterns in image data. Alongside cnns, other advanced models and techniques further enhance object recognition capabilities.

CNNs are widely used for object recognition due to their layered architecture, which mimics the visual processing structure of the human brain. Each layer in a CNN extracts different features from the image, progressing from simple patterns like edges to more complex shapes and objects. The main components of CNNs for object recognition are *Convolutional Layers* (these apply filters (or kernels) to input images, creating feature maps that highlight specific aspects like edges, textures, or colors); *Pooling Layers* (reduce the dimensionality of feature maps, making computation more efficient while retaining essential features); *Fully Connected Layers* (at the end of the network, these layers combine the extracted features to classify the image or detect objects within it). Popular CNN architectures like VGG, ResNet, and Inception have achieved high accuracy in object recognition tasks. They are often pre-trained on large datasets such as ImageNet and can be fine-tuned for specific tasks, allowing for quicker and more accurate recognition in various applications.

Object recognition is a core computer vision capability enabled by CNNs and advanced models like R-CNN, SSD, YOLO, and transformer-based detectors. These algorithms allow for efficient, real-time detection and recognition of objects in various settings, enhancing the accuracy and usability of computer vision across multiple industries [19].

2.2. Classification of images

Image classification is a fundamental task in computer vision, where the goal is to assign a label to an image based on its content. Classification can be performed using various approaches and criteria, such as categorizing objects, identifying emotions, or recognizing faces. Advanced machine learning and deep learning models, particularly convolutional neural networks (CNNs), have made it possible to classify images with high accuracy across different domains. There are some common approaches to image classification based on different criteria: Classification by Object Categories, Classification by Emotions, Classification by Facial Recognition and Identity, Classification by Scene Type, Classification by Image Quality or Content Style, Classification by Medical and Scientific Criteria (medical imaging, biometric classification etc.) [20].

3. IMPROVING THE IMAGE QUALITY

3.1. Noise suppression and increased clarity

Traditional methods for noise reduction often rely on filters that smooth out random variations in pixel intensity while trying to maintain important image details [16,18]. *Gaussian filtering* is one of the simplest and most commonly used techniques. A Gaussian filter smooths an image by averaging pixel values around each point, which helps reduce high-frequency noise. However, it can also blur edges if applied too heavily, so it's best used on images with mild noise. Unlike Gaussian filtering, which averages surrounding pixels, *Median filtering* replaces each pixel value with the median value of its neighborhood. This method is particularly effective for salt-and-pepper noise (random black and white specks) and does a better job of preserving edges, making it useful for noisy images that require sharp boundaries. *Bilateral filtering* not only smooths the image but also considers intensity differences, so it reduces noise while keeping edges intact. This filter is popular for images where maintaining edge sharpness is essential, such as in portrait or landscape photography.

Advanced noise suppression with deep learning

Deep learning models have significantly advanced noise suppression, especially for images with complex or heavy noise [17-20]. *Denoising autoencoders* are trained to identify noise in images and remove it. During training, images are intentionally corrupted with noise, and the model learns to reconstruct the clean version of the image. Denoising autoencoders work well on various types of noise, including gaussian and speckle noise, and are widely used in fields like medical imaging.

Denoising convolutional neural networks (DNCNN) is a deep learning model specifically designed for noise suppression. The network identifies patterns associated with noise, allowing it to retain important image details. Dncnn is especially useful for processing low-quality images, such as surveillance footage or low-light photos, where traditional filtering methods may not be effective.

Generative adversarial networks (GANS) can be used for both denoising and resolution enhancement. In noise suppression, gans work by training one network to generate clear, denoised images while another network judges their quality. This technique is effective for complex noise patterns, particularly in applications like photography restoration.

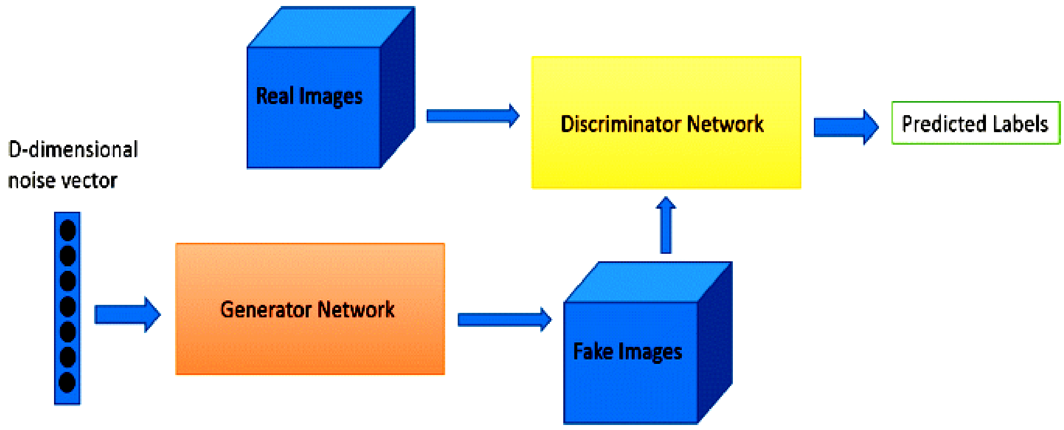

Figure 3 – Overview of GAN structure

Clarity enhancement involves bringing out finer details in an image, which can help with both aesthetic quality and information clarity. *Unsharp masking* improves clarity by boosting contrast around edges. A blurred copy of the image is subtracted from the original, and the result emphasizes sharp features. This method is commonly used in photography to make images look crisper. *High-pass filtering* works by letting only high-frequency elements (fine details) pass through while suppressing low-frequency components. This approach is used to enhance textures and fine structures without increasing noise. *Single-image super-resolution* models, often powered by deep learning, reconstruct high-resolution images from low-resolution inputs. These techniques are especially useful for enhancing details in small or blurry images. Super-resolution has practical applications in satellite imagery, medical scans, and even old photo restoration. *Deconvolution techniques* are used to reverse blurring in images, whether caused by motion, out-of-focus lenses, or atmospheric distortions. By estimating and removing this blur, deconvolution can bring out sharper details, making it a valuable tool in fields like astronomy and microscopy [17,19, 20].

Noise suppression and clarity enhancement transform low-quality images by reducing noise and restoring lost details. Traditional filtering methods like Gaussian and median filters are still useful for simple noise patterns, while deep learning models such as DnCNN and GANs excel in more complex cases. Together, these techniques make images sharper, clearer, and more informative across various fields.

3.2. Super resolution and recovering damaged images

Super resolution and recovering damaged images are important techniques in image processing, used to improve image quality and restore lost or blurred details. These techniques are widely applied in photography, video, medical imaging, and historical preservation [18].

Super resolution is the process of enhancing the resolution of an image, making it sharper and more detailed. This can be especially helpful when working with low-resolution images that need to be enlarged or when fine details are needed. *Single Image Super Resolution (SISR)* algorithms take a single low-resolution image and increase its resolution. Deep learning models, especially Convolutional Neural Networks (CNNs), are often used for this purpose. For example, models like SRCNN (Super-Resolution CNN) and SRGAN (Super-Resolution Generative Adversarial Network) have been trained to recognize patterns in low-resolution images and add realistic details when enlarging them [12,17-20].

Recovering damaged images involves repairing or reconstructing images that have parts missing, are blurred, or contain artifacts (errors or distortions). *Image inpainting* fills in missing or damaged parts of an image by predicting what should be in those areas based on surrounding pixels. This technique is especially useful for old photos that have been torn, faded, or scratched. Deep learning methods, like inpainting models using GANs, can learn to generate realistic-looking content in damaged areas. *Deblurring technique* removes blur caused by motion, out-of-focus cameras, or other factors. Deblurring algorithms attempt to identify and reverse the blur, restoring sharpness to the image. CNNs and deconvolution techniques are commonly used to achieve this. *Denoising* is used to remove unwanted noise (random specks or graininess) from images, which is especially common in low-light or older images. Denoising algorithms, such as DnCNN, can effectively reduce noise while keeping important details intact [20].

Figure 4 – Example of using AI Deblurring in real time

Super resolution and image recovery bring out hidden details and restore clarity in low-quality or damaged images. Whether using SISR to enhance resolution or inpainting and deblurring techniques to repair damages, these methods make a big impact in improving image quality across various fields, from photography to medical imaging.

4. GENERATION AND MODIFICATION OF IMAGES USING AI

4.1. Generative adversarial networks (GANs)

Image generation refers to the process of creating new images that look realistic or artistic, often from nothing more than a description or a rough sketch. This process is possible using Generative Adversarial Networks (GANs) and diffusion models. *GANs* are used to create synthetic images of people, places, or objects for video games, advertisements, or fashion, where realistic visuals are essential but hiring models or setting up photoshoots may be too costly.

Diffusion models gradually add random noise to images and then learn to remove this noise, creating sharp, high-quality images. These models are used by tools like DALL-E and Stable Diffusion, which are known for transforming text descriptions into detailed images. Diffusion models are popular for creating visual content based on textual prompts, allowing users to generate customized artwork or concept images by simply describing them in words [14,17,19].

4.2. Style transfer using AI

AI can also modify existing images, either by transforming the style, adjusting colors and textures, or changing key elements while keeping the original image structure. Style transfer allows AI to apply the style of one image (such as a famous painting) onto another image, keeping the content while altering the artistic style. Style transfer is often used in photography and design to create unique, eye-catching visuals that combine realism with artistic flair. Style transfer might be used by graphic designers to give a landscape photo the look of van gogh's "starry night" or monet's impressionist style, transforming everyday scenes into artworks.

Figure 5 – Example of using Style Transfer using AI technology

AI can enhance the resolution of an image, making low-resolution images clearer and more detailed. This technique is especially useful for enhancing old photos, zooming in on images without losing quality, or preparing images for high-resolution displays [19]. Image upscaling tools are commonly used in video production to enhance the quality of footage shot in low resolution, making it suitable for HD and 4K displays [20].

5. APPLICATION OF AI TO WORK WITH IMAGES IN DIFFERENT AREAS

5.1. Medicine

In medicine AI plays a critical role in analyzing medical images such as X-rays, MRIs, and ultrasounds. Advanced AI models, particularly those using deep learning and convolutional neural networks (CNNs), are trained to recognize patterns associated with specific diseases, aiding in early diagnosis and treatment planning. AI algorithms can analyze chest X-rays to detect conditions like pneumonia, tuberculosis, and even early signs of lung cancer. By identifying abnormalities that might be missed by the human eye, AI assists radiologists in making faster and more accurate diagnoses. MRI Interpretation scans provide detailed images of internal structures, which are often complex and challenging to interpret. AI helps highlight areas of concern, such as tumors or lesions in the brain, and can even track changes over time. This technology is widely used in neurology and oncology for monitoring disease progression. AI enhances the clarity of ultrasound images and helps classify different types of tissues or masses [16,20]. For example, in prenatal care, AI can help identify fetal anomalies, while in cardiology, it can assist in visualizing heart structures to detect conditions like valve defects or blood flow irregularities. By automating parts of the diagnostic process, AI not only speeds up healthcare delivery but also improves diagnostic accuracy, enabling doctors to provide better, more personalized care.

5.2. Art and culture

AI is revolutionizing the field of art and culture by helping restore damaged artworks, analyze artistic styles, and even create new works of art. These applications of AI bring new possibilities for cultural preservation, understanding, and creativity. For damaged or aged paintings, AI can assist in restoration by reconstructing missing parts based on the original artist's style. For example, AI algorithms analyze undamaged areas of a painting to predict how missing sections should appear, ensuring historical accuracy. Art historians use

AI to analyze patterns in artistic styles across different periods and regions. By recognizing subtle stylistic features, AI can help identify the probable time period or even the specific artist behind an artwork. This has applications in art authentication, where AI assists in confirming the origins of a piece. Generative AI models, such as GANs, allow for the creation of entirely new artworks that mimic various artistic styles or combine different influences. AI-generated art is becoming popular in both digital and physical spaces, as it provides artists with inspiration and even collaborative opportunities to create unique, modern pieces. AI in art and culture opens doors for preserving heritage, analyzing historical trends, and inspiring modern creativity by blending traditional techniques with cutting-edge technology.

Figure 6 – Example of using DeepArt and Generative AI in Art.

5.3. Industry and security

In industry and security AI supports quality control, defect analysis, and facial recognition, all of which are crucial for maintaining standards and ensuring safety. AI-driven automation and recognition systems help increase efficiency and accuracy in these areas. AI is widely used in manufacturing to monitor the quality of products, especially in sectors like electronics and automotive. By scanning products for tiny defects or inconsistencies, AI ensures that only products meeting strict quality standards move forward in production. AI can detect issues that human inspectors might miss, such as micro-cracks or minor shape deviations. AI algorithms can identify specific types of defects in materials or products, helping manufacturers understand common faults and prevent them in future batches. For instance, in semiconductor manufacturing, AI helps detect surface flaws or structural anomalies that could impact performance. AI-based facial recognition systems are used for access control in high-security areas or for identifying individuals in large crowds. These systems are designed to match facial features with a database of authorized personnel or to detect known threats in public spaces, adding an extra layer of security in both corporate and public environments. Through these applications, AI helps industries reduce errors, enhance safety, and maintain high-quality standards, ultimately leading to safer products and environments.

5.4. Marketing and entertainment

AI powers content creation, such as virtual models, image modification, and personalized ads, creating more engaging and customized experiences for consumers. AI-generated virtual models showcase clothing, accessories, or cosmetics in a realistic and adaptable way, often saving brands the cost of hiring human models. These digital models can be personalized to match specific demographics or preferences, helping brands reach diverse audiences and test product appeal. AI tools allow marketers to quickly modify images to fit different ad formats or styles. AI can adjust colors, lighting, and textures in images to match branding or make products look more appealing. For example, AI can retouch a model’s skin in a beauty ad or simulate various lighting effects in a product photo. AI is used to create and customize content that aligns with individual user preferences. This might include generating personalized video recommendations on streaming platforms, crafting unique ad visuals, or even composing music and soundscapes for immersive experiences. AI-driven tools give brands and creators a powerful way to enhance audience engagement through visually appealing and highly personalized content, helping build stronger connections with consumers.

AI applications in medicine, art, industry, and marketing demonstrate the versatility and impact of image-processing technology. From diagnosing diseases and restoring art to ensuring product quality and personalizing consumer experiences, AI enables new possibilities across various fields, enhancing both efficiency and creativity.

CONCLUSIONS

1. AI technologies have unlocked new capabilities in digital image processing, enabling applications that go beyond traditional methods, such as noise reduction, image enhancement, super-resolution, and inpainting. These advancements allow for higher-quality image analysis and manipulation, which benefit various sectors.
2. AI-powered image processing techniques are successfully applied across numerous fields, including healthcare, where they assist in medical diagnostics; the arts, where they enable cultural preservation and artistic innovation; industry, where they improve quality control and defect detection; and marketing, where they enhance content creation and customization.
3. Continued research and development in AI for image processing will likely lead to even more precise, accessible, and versatile tools, improving efficiency, accuracy, and creative possibilities. These advancements are expected to impact both current and emerging applications, driving further innovation across diverse domains.

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ДОСЛІДЖЕННЯ МОЖЛИВОСТЕЙ ВИКОРИСТАННЯ ТА ТЕХНОЛОГІЙ ОБРОБКИ ЦИФРОВОГО ЗОБРАЖЕННЯ: ОГЛЯД ТА ЗАСТОСУВАННЯ

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