

Bio-Inspired Mathematical Visual Models for Real-World Applications: A Systematic Review

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Abstract

Background: Mathematical models inspired by the Human Visual System (HVS) bridge the gap between biological perception and computer vision, by offering powerful frameworks for representing, enhancing, and analyzing digital images. From their initial development to contemporary applications, HVS models have demonstrated significant success in providing image-based solutions for complex real-world tasks. **Objective:** This work is an up-to-date systematic review of research on seven HVS models in real-world applications across six specific image processing tasks to evaluate, through five research questions, their contemporary relevance, adoption frequency, task-model preferences, and practical deployment domains. **Methods:** We systematically analyze seven prominent bio-inspired visual models across real-world applications: the Retinex Model (RM), Difference of Gaussians (DoG), Gabor Filters (GFs), Hermite and Steered Hermite Transforms (HT/SHT), the Steerable Pyramid (SP), Spiking Neural Networks (SNNs), and the Dual-Tree Complex Wavelet Transform (DT-CWT). Next, following the PRISMA guidelines, an initial literature search was performed in Scopus, yielding 595 publications published between 2020 and 2026, to assess the contemporary relevance of these visual models. From this initial search, 153 research works were selected based on the following inclusion criteria: (i) application to real-world image processing problems; (ii) coverage of at least one of six core image processing tasks: segmentation, watermarking/encryption, motion analysis and robotics, classification, pattern recognition, and enhancement; (iii) utilization of at least one of the seven mathematical visual models; (iv) document types restricted to peer-reviewed journal articles and book chapters; and (v) publications in the English language. Additionally, studies were excluded based on the following criteria: (i) focus on non-visual or non-image-based applications; (ii) utilization of alternative HVS models (e.g., Fourier log-polar mapping, Naka-Rushton photoreceptors, or Hopfield-based cortical networks); (iii) document types restricted to conference papers, editorials, and reviews; and (iv) publications written in languages other than English. Thus, through a systematic methodology, (a) the mathematical visual models were formally described by highlighting their biological foundations, analyzing their computational complexity and noise robustness, and outlining their recent developments in computer vision applications; (b) the selected publications were analyzed to show their statistical distribution across the seven models, publication modalities, and primary image processing tasks; and (c) the selected works were evaluated in terms of their distribution by model and year (via arithmetic mean, standard deviation, adjusted Fisher-Pearson skewness coefficient, and heatmaps), citation distribution, *h*-index, and mapping across real-world applications and specific vision tasks. **Results:** This study reveals that the mathematical visual models mimic distinct HVS stages and represent diverse receptive field structures. Additionally, this work finds that GFs, the HT/SHT, the SP, and the DT-CWT exhibit a high level of noise robustness, whereas GFs, the SP, and SNNs



Academic Editor: Vladimir Balan

Received: 17 July 2026

Revised: 3 September 2026

Accepted: 29 September 2026

Published: 2 October 2026

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are the most elaborate bio-inspired visual models owing to their complex implementation steps and high parameter count. In contrast, the RM, DoG, and DT-CWT achieve the lowest computational complexity, but with limited image decomposition capabilities, while the HT/SHT offers competitive computational complexity alongside rich image decomposition capabilities. Conversely, RM and SNNs display the highest publication activity from 2020 to 2026 alongside notable temporal volatility, whereas GFs and DT-CWT maintain a stable yet dynamic trajectory across the same period. Moreover, studies employing DT-CWT, GFs, and SNNs exhibit sustained productivity and substantial domain impact, attaining *h*-index values of 10, 9, and 8, respectively. Regarding real-world applications, GFs represent the most widely deployed visual model (24.8%), followed by RM and SNNs with 20.3% and 19.6%, respectively. Task-specific analysis reveals distinct model specializations: RM leads in image enhancement (60%) and pattern recognition (33.3%) owing to its intrinsic color constancy properties, while GFs are predominantly selected for segmentation (44.4%) and classification (42.1%). Furthermore, DT-CWT and HT/SHT dominate watermarking and encryption applications (66.7%), whereas SP, SNNs, and RM serve as primary choices for motion analysis and robotics, representing 27.3% (SP) and 22.7% each (SNNs and RM) of task deployments. Regarding medical imaging, 33 (21.5%) of the 153 selected studies target diagnostic support or e-health applications. Within this domain, HT/SHT demonstrates the highest relative concentration, with 50% (5 out of 10) of its publications dedicated to medical applications. Conclusions: By systematically mapping the evolutionary trends and adoption metrics of these visual models across six primary vision tasks (segmentation, watermarking/encryption, motion analysis and robotics, classification, pattern recognition, and image enhancement) this work highlights current model specializations and application domains. Visual model selection depends on domain demands. Security utilizes transform-domain models (DT-CWT, HT/SHT); robotics requires spatiotemporal processing (SP, SNNs); segmentation and classification favors GFs and SNNs; and RM and GFs dominate enhancement and feature extraction. The resulting synthesis provides a clear taxonomy to guide future developments in bio-inspired computer vision. Finally, due to the wide diversity of implementation frameworks across the evaluated models and application domains, standardized empirical benchmarking of operational trade-offs and hardware metrics was beyond the scope of this review. These aspects represent promising avenues for future research, which will evaluate these technical parameters within dedicated, task-specific studies.

Keywords: Difference of Gaussians; Dual-Tree Complex Wavelet Transform; Gabor Filters; Hermite Transform; human visual system; mathematical visual models; receptive fields; Retinex Model; Steered Hermite Transform; Spiking Neural Networks; Steerable Pyramid; real-world applications

MSC: 68U10; 68Q07; 68T45

1. Introduction

Within the animal kingdom, the mammalian visual system demonstrates a remarkable ability to resolve continuous features, edge boundaries, and spatial orientations despite significant levels of visual interference. This capability allows mammalian species to interpret electromagnetic radiation with exceptional speed, efficiency, and clarity. In the fields of computer vision and image processing, modeling the Human Visual System (HVS) has evolved from simple heuristic filters to rigorous mathematical transforms. These

mathematical models emulate biological processes, such as those occurring during early retinal processing and in complex cortical computations.

Mathematical models inspired by the HVS bridge the gap between biological perception and computer vision, offering powerful frameworks for representing, enhancing, and analyzing digital images. Consequently, bio-inspired visual models exploit the constraints in the HVS as the luminance adaptation and edge enhancement (early retinal processes), multiscale analysis, orientation selectivity, shift-invariance, and temporal neural representation (cortical processes), allowing to optimize image processing tasks like edge detection, noise reduction, and image compression.

Several bio-inspired mathematical visual models are widely utilized, such as the Retinex Model (RM), Difference of Gaussians (DoG), Gabor Filters (GFs), Hermite Transform (HT) / Steered Hermite Transform (SHT), Steerable Pyramid (SP), Spiking Neural Networks (SNNs), and the Dual-Tree Complex Wavelet Transform (DT-CWT). There are other bio-inspired in HVS models that we excluded from this work. Although these models with stricter biological fidelity are present in the literature such as Cortex filter banks full biophysical retina simulations [1], their adoption in digital image processing remains marginal. This is due to their prohibitive computational cost, lack of invertibility, and high parametric sensitivity, which hinders their generalization. In addition to Cortex filter banks, other biologically detailed models—such as the bioethical Naka-Rushton photoreceptor equations [2], Fourier-Mellin log-polar mappings [3], and Hopfield-based cortical networks [4] have seen limited practical adoption. While these models offer physiological fidelity, they suffer from severe drawbacks including irreversible spatial distortion, slow convergence in recurrent dynamics, and prohibitive computational overhead. Particularly, to ensure a robust, computationally feasible, and state-of-the-art framework, explicit inclusion and exclusion criteria were established for the candidate Human Visual System (HVS) representations. Out of the broader spectrum of bio-inspired algorithms, models were systematically excluded based on three primary mathematical and operational limitations:

- **High Computational Complexity and Non-Linearity:** Biologically detailed retinal models, such as the Naka-Rushton equations, require the numerical integration of non-linear differential equations per pixel. These were excluded due to their prohibitive computational overhead, as their dynamic range compression benefits are efficiently achieved by computationally lighter frameworks like Retinex and Difference of Gaussians.
- **Spatial Artifacts and Rigid Structural Constraints:** Block-based perceptual masking models (e.g., Watson's DCT-based JND) and rigid Cortex filter banks were omitted due to their susceptibility to blocking artifacts and lack of continuous, shift-invariant multiresolution analysis. Advanced continuous transforms, such as the Dual-Tree Complex Wavelet Transform and Hermite Transform, supersede these rigid architectures.
- **Irreversible Spatial Distortion:** Retinotopical log-polar mappings (e.g., Fourier-Mellin transform) simulate foveated vision at the expense of severe peripheral resolution loss and irreversible spatial transformation, rendering them unsuitable for full-frame feature preservation compared to Steerable Pyramids and Gabor wavelets.

In contrast, the models selected in this work represent the optimal trade-off in the literature: they represent the most mathematically valuable perceptual properties—such as directional selectivity and multiscale response—under computationally efficient, stable, and directly applicable formulations for real-world systems.

The Retinex (Retina and cortex) Model emulates the combined biological mechanisms of the retina and the cerebral cortex, specifically their center-surround opponent receptive fields. It simulates color constancy, the ability of the HVS to perceive stable object colors and lightness despite severe, non-uniform shifts in the environmental illumination [5].

The DoG operator mimics the antagonistic center-surround receptive fields of retinal ganglion cells. These cells exhibit concentric circular receptive structures where light falling on the center excites (or inhibits) the cell, while light on the surround triggers the opposite response (e.g., an on-center/off-surround configuration) [6].

Another relevant visual model is the Gabor Filter framework, which emulates the receptive field profiles of simple cells in the primary visual cortex (striate cortex, area V1). Physiologically, these cells function as linear spatial filters characterized by alternating, parallel excitatory and inhibitory stripes [7].

Furthermore, the Hermite Transform is a polynomial transform that models the localized, multiscale analysis of visual geometry performed by cortical receptive fields, utilizing derivatives of Gaussian window functions [8,9]. A primary advantage of the HT is its ability to ensure perfect image reconstruction through the inverse transform. Moreover, it expands the local image signal over a basis of strictly orthogonal Hermite polynomials modulated by a symmetric Gaussian window. This orthogonal framework overcomes the spatial localization limitations inherent to the non-orthogonal nature of GFs [8].

The Steered Hermite Transform is a variant of the HT that adaptively rotates toward the local orientation of image contours [8]. Consequently, the SHT concentrates the local image energy into a highly compact set of one-dimensional directional coefficients [10].

Another key bio-inspired mathematical visual model is the SP, a multiscale, multi-orientation linear decomposition that models cortical multi-resolution visual processing as a local Taylor series expansion [11]. This model overcomes the sub-band aliasing and poor diagonal selectivity inherent to standard orthogonal wavelet transforms.

SNNs model the biological nervous system's synaptic dynamics and temporal spike propagation with the exceptional physiological fidelity [12,13]. These networks emulate how the retina converts analog light intensities into discrete, asynchronous electrical impulses (action potentials) that are subsequently transmitted through excitatory and inhibitory synapses [13,14].

The DT-CWT models the highly directional visual channels of human cortical processing, addressing the critical limitations of standard wavelets, which suffer from severe shift-sensitivity (aliasing) and poor diagonal selectivity. DT-CWT resolves these issues by utilizing two parallel trees of real biorthogonal filters (Tree A and Tree B). These trees represent the real and imaginary parts of complex analytic wavelet coefficients, and function as complex Gabor-like filters. This architecture enables the transform to achieve approximate shift-invariance and true directional selectivity orientations with very low redundancy (4:1 in 2D) and perfect reconstruction [15,16].

This study presents an up-to-date systematic literature review of publications spanning from 2020 to 2026, focusing on seven HVS models in real-world applications across six specific image processing tasks to evaluate, through five research questions, their contemporary relevance, citation distribution, adoption frequency, task-model preferences, and practical deployment domains. Additionally, the mathematical visual models were formally described by highlighting their biological foundations, analyzing their computational complexity and noise robustness, and outlining their recent developments in computer vision applications.

The contributions of this review are summarized as follows:

- To the best of our knowledge, this represents the first systematic review to analyze these relevant bio-inspired mathematical visual models collectively within a single unified study. Although several comprehensive surveys exist in the literature, they analyze HVS models within a specific domain. Specifically, prior reviews focus on some subfields separately: multiscale directional transforms (DT-CWT [17], Steerable Pyramids [18], Gabor Filters [19], Hermite Transform [20]), perceptual contrast and color

constancy (Retinex Model and DoG) [21,22], or temporal event-driven neuromorphic frameworks (SNNs model) [23]. No single unified review exists that systematically categorizes, compares, and evaluates the seven most widely adopted HVS representations—spanning from early retinal processing (DoG, Retinex) and V1 cortical representations (Gabor, Hermite, Steerable Pyramids, DT-CWT) to spatio-temporal spiking dynamics (SNNs). This work fills this critical gap by providing a taxonomy, trade-off analysis, and computational benchmark across all these models.

- This review performs a comprehensive mapping of the temporal trends, task-specific specializations, and real-world deployment scenarios of the bio-inspired mathematical visual models evaluated.
- This review compares the HVS-inspired visual models based on their mathematical foundations, computational complexity, noise robustness level, and parameter requirements. Finally, a comparative analysis of these visual models in the medical domain, covering both diagnostic support and e-health applications, is provided.

The remainder of this paper is outlined as follows. Section 3 provides the mathematical foundation of the bio-inspired mathematical visual models reported in this review. Section 4 details the review methodology used, while Section 5 presents the main results. Furthermore, Section 6 provides a comprehensive discussion of the findings, and Section 7 concludes the paper.

2. Related Reviews

Several reviews have been published that address the HVS models including DoG, Retinex, Gabor, Hermite, Steerable Pyramids, DT-CWT and SNNs that analyze only a group of the models. Below we summarize relevant reviews in terms of scope:

- Selesnick et al. [17] provide a theoretical review from the DT-CWT, showing how complex wavelets with good properties can be designed, and illustrates a range of applications in signal and image processing. No review method as PRISMA has included in the review. The article reviewed applications up to 2005.
- Reiser et al. [18] reviewed the design and application of complex steerable filter banks for extracting rotation-invariant features in image analysis. It categorizes equivariant representation theory (steerability), focusing on applications such as oriented pattern detection, local spatial structure estimation, texture classification, and 2D/3D biomedical image processing. The study does not follow the PRISMA methodology. The article reviewed applications up to 2009.
- Chen et al. [19] provides a systematic review on the application of Gabor wavelets in face recognition, highlighting their ability to handle illumination, expression, and pose variations. The survey focuses on practical applications such as facial landmark detection, local-global feature extraction, and compact representation for biometric security systems. Notably, the study does not employ the PRISMA methodology. The article surveys applications up to 2006.
- Martens [20] presents a comprehensive overview of the Hermite Transform as a perceptual, multiscale image representation based on Gaussian derivatives and orthogonal polynomials. The survey focuses on applications such as image de-noising, image fusion, motion estimation, image deblurring, contrast enhancement, image indexing, image coding, image quality prediction, and modeling of the human visual system. The study does not use PRISMA methodology. The applications present in this article are up to 2004.
- Lin and Kuo [22] present a comprehensive review of perceptual metrics for human Image Quality Assessment (IQA). The authors review several visual decomposition models, including GFs, Cortex filters, wavelets, Gaussian pyramids, and SP filters.

However, this study does not employ a PRISMA systematic protocol, and its references are limited to studies published up to 2010.

- Gallego et al. [23] addresses the Spiking Neural Network framework and biomimetic asynchronous processing (dynamic vision sensors). The review covers algorithms for motion estimation, feature tracking, 3D reconstruction, and neuromorphic control. The study does not employ the PRISMA systematic protocol and the references are up to 2020.

Although previous reviews have contributed to the field, none addressed the seven HVS models at the same time included in this work. Only the work of Lin and Kuo [22] includes GFs, and SP filters. Besides, none of the works used the PRISMA methodology as guide.

3. Bio-Inspired Mathematical Visual Models

This section presents an overview of seven mathematical visual models inspired by the human visual system. The following subsections detail the operational principles, mathematical foundations, and structural characteristics of the Retinex Model, Difference of Gaussians, Gabor Filters, the Hermite Transform and Steered Hermite Transform, the Steerable Pyramid, Spiking Neural Networks, and the Dual-Tree Complex Wavelet Transform.

3.1. The Retinex Model

The Retinex Model [24] was proposed by Land and McCann in 1971 and it was one of the first mathematical visual models inspired by the mechanisms of human visual perception of brightness and color. By compensating for illumination variations, it generates color images with greater fidelity that more closely resemble how a scene is perceived by the human eye, resulting in richer and more natural visual information.

Retinex algorithms are designed to recover and preserve color information regardless of illumination conditions. In addition, they enhance image quality by improving visual attributes such as brightness and contrast, particularly in images acquired under low-light environments [25]. Equation (1) shows the Single-Scale Retinex (SSR) :

$$R(x, y) = \log[I(x, y)] + \log[G(x, y, \sigma) \otimes I(x, y)], \quad (1)$$

where $I(x, y)$ is a grayscale image, $\otimes$ denotes the convolution operation, and $G(x, y, \sigma)$ is a Gaussian function defined as follows:

$$G(x, y, \sigma) = z \cdot \exp - \frac{x^2 + y^2}{2\sigma^2}, \quad (2)$$

where σ^2 is the variance and $z = \frac{1}{2\pi\sigma^2}$ represents a normalization factor.

Equation (1) shows that convolving the original image with a Gaussian filter provides an estimate of the illumination component through a mathematical blurring process.

On the other hand, the Multi-Scale Retinex (MSR) is a extension of the SSR algorithm, which evaluates Retinex values over multiple scales and merges the results [25]:

$$R_{MSR} = \sum_{s=1}^{N_s} \omega_s R(x, y), \quad (3)$$

where $\omega_s = 1/3$ is the scale-wise weight and $N_s = 3$.

MSR is employed for color recovery, contrast enhancement, and dynamic range compression in scenes with poor or uneven illumination. Additionally, it is widely utilized to

improve the repeatability of local gradient-based feature extractors, such as Scale-Invariant Feature Transform (SIFT) [25].

3.2. Difference of Gaussians

The Difference of Gaussians method has its origins in neuroscience for modeling biological vision and it was formally introduced into the field of computer vision and image processing by Marr et al. [6]. The authors demonstrated that the subtraction of two Gaussian filters serves as an efficient mathematical approximation of the Laplacian of Gaussian (LoG) operator for detecting edges via zero-crossings. Later, Lower et al. [26] proposed the use of DoG by integrating it as the foundational step for keypoint detection in the SIFT algorithm.

The DoG method involves the subtracting of one blurred version of an image from another, more blurred version.

To smooth a two-dimensional image $I(x, y)$, a normalized Gaussian kernel $G(x, y, \sigma)$ is used:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), \quad (4)$$

where σ represents the standard deviation.

The representation of the image in the scale space, denoted as $L(x, y, \sigma)$, is obtained by the convolution ($\otimes$) of the original image $I(x, y)$ with the Gaussian kernel at a specific scale σ :

$$L(x, y, \sigma) = G(x, y, \sigma) \otimes I(x, y). \quad (5)$$

Expressed in the continuous domain, the convolution is defined as:

$$L(x, y, \sigma) = \iint_{-\infty}^{\infty} I(u, v) G(x - u, y - v, \sigma) du dv. \quad (6)$$

Therefore, the DoG function, $D(x, y, \sigma)$, is defined as the difference between two adjacent scale-space representations separated by a constant factor k :

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma). \quad (7)$$

This can also be expressed as the convolution of the image with the difference of the two Gaussian kernels:

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) \otimes I(x, y). \quad (8)$$

The DoG acts as a computationally efficient approximation of the Laplacian of Gaussian ($\nabla^2 G$).

On the other hand, from the linear diffusion equation, we know that:

$$\frac{\partial G}{\partial \sigma} = \sigma \nabla^2 G. \quad (9)$$

If we approximate the partial derivative with respect to σ using finite differences, we get:

$$\frac{\partial G}{\partial \sigma} \approx \frac{G(x, y, k\sigma) - G(x, y, \sigma)}{k\sigma - \sigma} = \frac{G(x, y, k\sigma) - G(x, y, \sigma)}{(k - 1)\sigma}. \quad (10)$$

Equating both expressions yields:

$$\frac{G(x, y, k\sigma) - G(x, y, \sigma)}{(k - 1)\sigma} \approx \sigma \nabla^2 G. \quad (11)$$

Multiplying both sides by $(k - 1)\sigma$:

$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k - 1)\sigma^2 \nabla^2 G. \quad (12)$$

Therefore, the DoG function is directly related to the Laplacian through a scale constant:

$$D(x, y, \sigma) \approx (k - 1)\sigma^2 \nabla^2 L(x, y, \sigma). \quad (13)$$

3.3. Gabor Filters

Dennis Gabor [27], proposed Gabor Filters by introducing the functions within the context of one-dimensional signal analysis to demonstrate how a signal could be optimized and analyzed simultaneously in both the time and frequency domains. Later, Daugman [7] extended the mathematical formalism to two dimensions to model the receptive fields of simple cells in the mammalian primary visual cortex (V1), popularizing their widespread application in modern digital image processing and computer vision.

The Gabor Filters are based on the modulation of a complex harmonic wave by a Gaussian envelope function. The Gabor Filters are non-orthogonal functions that achieve maximum joint resolution in both the spatial and frequency domains, bounded by the Heisenberg uncertainty principle.

The spacial formulation is based on the impulse response function of a two-dimensional Gabor filter defined as:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \psi\right). \quad (14)$$

where x' and y' represent the rotated coordinates based on the orientation of the filter:

$$x' = x \cos \theta + y \sin \theta \quad (15)$$

$$y' = -x \sin \theta + y \cos \theta. \quad (16)$$

The physical interpretation parameters is as follows:

- λ (wavelength): handle the stripe spacing of the sinusoidal wave. Typically expressed in pixels (usually ≥ 2) and directly scales the filter.
- θ (orientation): Specifies the normal direction to the parallel stripes of the Gabor function. It modulates which edge angles or structural textures the filter will detect (e.g., $0^\circ, 45^\circ, 90^\circ$).
- ψ (phase offset): Defines the phase of the harmonic carrier wave.
 - If $\psi = 0^\circ$ or 180° , the filter is symmetric (real part), which is optimal for detecting lines or structural centers.
 - If $\psi = \pm 90^\circ$, the filter is asymmetric (imaginary part), which is ideal for detecting edge transitions.
- σ (standard deviation): Determines the spatial variance of the Gaussian envelope, thereby defining the size of the neighborhood or spatial support region of the filter.
- γ (spatial aspect ratio): Defines the ellipticity of the Gaussian support. If $\gamma = 1$, the spatial support is circular; if $\gamma < 1$, the filter stretches perpendicularly relative to the parallel stripes.

The complex analytic formulation extract both the magnitude and phase response of the spatial domain simultaneously:

$$h(x, y) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp\left(i\left(2\pi \frac{x'}{\lambda} + \psi\right)\right). \quad (17)$$

By applying Euler's identity, this complex filter can be seamlessly separated into its real and imaginary components.

Thus, the 2D spatial convolution between an image $I(x, y)$ and the 2D Gabor filter $g(x, y; \lambda, \theta, \psi, \sigma, \gamma)$ is defined as:

$$\mathcal{I}(x, y) = \left[\exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \right] \otimes I(x, y). \quad (18)$$

An important property of the Gabor Filters is that its Fourier Transform is also a Gaussian distribution, but shifted to the frequency of the carrier wave. Consequently, it behaves as a highly localized band-pass filter.

The 2D Fourier Transform of the complex analytic function $h(x, y)$ is expressed in the frequency domain (u, v) as:

$$H(u, v) = 2\pi \frac{\sigma^2}{\gamma} \exp\left(-\frac{\sigma^2}{2} \left[(u' - F)^2 + \frac{v'^2}{\gamma^2}\right]\right), \quad (19)$$

where $F = \frac{1}{\lambda}$ represents the central frequency magnitude of the carrier, while u' and v' are the rotated spatial frequencies:

$$u' = u \cos \theta + v \sin \theta, \quad (20)$$

$$v' = -u \sin \theta + v \cos \theta. \quad (21)$$

3.4. Hermite Transform/Steered Hermite Transform

The Hermite Transform was proposed in 1990 by Martens [9,28]. It is a bio-inspired mathematical image representation model that incorporates the computational properties of early human vision. HT reproduces fundamental characteristics of the mammalian visual system by modeling retinal receptive fields as overlapping Gaussian functions and V1 receptive fields as Gaussian derivatives. One of the main advantage of HT is its ability to achieve perfect image analysis and reconstruction, which makes it especially suitable for image synthesis applications.

To decompose a grayscale image $I(x, y)$, the HT analyzes the visual information using a Gaussian window function with unit energy with respect to $v^2(x, y)$ (Equation (22)):

$$v(x, y) = \frac{1}{\sigma\sqrt{\pi}} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), \quad (22)$$

where σ^2 represents the variance of the Gaussian window.

Following, the localized information is expanded to a family of polynomials $G_{m,n-m}(x, y)$ orthogonal to the Gaussian window function (Equation (23)).

$$G_{m,n-m}(x, y) = \frac{1}{\sqrt{2^n m!(n-m)!}} H_m\left(\frac{x}{\sigma}\right) H_{n-m}\left(\frac{y}{\sigma}\right), \quad (23)$$

where m and $(n - m)$ represent the analysis order in the spatial directions x and y , with $n = 0, \dots, \infty$ and $m = 0, \dots, n$, and H_n are the generalized Hermite polynomials.

The generalized Hermite polynomials are generated via a variation Rodrigues' formula for the Hermite polynomials (Equation (24)):

$$H_n\left(\frac{x}{\sigma}\right) = (-1)^n \exp\left(-\frac{x^2}{\sigma^2}\right) \frac{d^n}{dx^n} \exp\left(-\frac{x^2}{\sigma^2}\right). \quad (24)$$

The Hermite coefficients $I(x, y)_{m,n-m_i}$ are calculated by convolving the RGB image $I(x, y)$ with the Hermite analysis filters $D_{m,n-m}(x, y)$ followed by a sub-sampling (T) (Equation (25)):

$$I_{m,n-m}(x_0, y_0) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(x, y) D_{m,n-m}(x_0 - x, y_0 - y) dx dy, \quad (25)$$

where (x_0, y_0) is the spatial position in the sampling lattice S and the separable Hermite analysis filters (Equation (27)) are defined by:

$$D_{m,n-m}(x, y) = D_m D_{n-m} = G_{m,n-m}(-x, -y) v^2(-x, -y) \quad (26)$$

$$D_k(x) = \frac{(-1)^k}{\sqrt{2^k k!}} \frac{1}{\sigma \sqrt{\pi}} H_k\left(\frac{x}{\sigma}\right) \exp\left(-\frac{x^2}{\sigma^2}\right), \quad (27)$$

with $k = 0, 1, 2, \dots, \infty$.

Finally, the inverse Hermite Transform reconstructs the original image from the Hermite coefficients using the Hermite synthesis filters $P_{m,n-m}$ (Equation (28)):

$$I(x, y) = \sum_n \sum_{n=0}^n \sum_{(x_0, y_0) \in S} I_{m,n-m}(x_0, y_0) \cdot P_{m,n-m}(x - x_0, y - y_0), \quad (28)$$

where $V(x, y)$ is the weight function:

$$V(x, y) = \sum_{(x_0, y_0) \in S} v^2(x - x_0, y - y_0) \neq 0 \quad (29)$$

and

$$P_{m,n-m}(x, y) = \frac{D_{m,n-m}(x, y)}{V(x, y)}. \quad (30)$$

On the other hand, in 1997, van Dijk and Martens [10] introduced the Steered Hermite Transform, which is obtained by rotating the Hermite coefficients by an angle θ of maximum energy (Equation (31)), e.g., the gradient direction.

$$I_{n,\theta}(x_0, y_0) = \sum_{k=0}^n \left(I_{k,n-k}(x_0, y_0) \right) \left(\Phi_{k,n-k}(\theta) \right), \quad (31)$$

where $\Phi_{m,n-m}(\theta)$ represents the angular functions (Equation (32)):

$$\Phi_{m,n-m}(\theta) = \sqrt{\binom{n}{m}} \left(\cos^m(\theta) \right) \left(\sin^{n-m}(\theta) \right). \quad (32)$$

By applying this rotation in the SHT, local image energy is highlight concentrate into a set of one-dimensional directional coefficients, which is exceptionally powerful for anisotropic noise reduction (smoothing along, rather than across, boundaries) [8], progressive image compression [10], and local feature classification (edges, lines, and junctions) [8].

In 2006, Silván-Cárdenas and Escalante-Ramírez [8] proposed both the Multiscale Hermite Transform (MHT) and the Steered Multiscale Hermite Transform (SMHT), alongside an efficient pyramidal implementation framework.

3.5. Steerable Pyramid

In 1995, Simoncelli et al. [11] introduced the Steerable Pyramid, an image decomposition that captures both scale and orientation, which is based on a pyramid decomposition and derivative operations.

In the SP, the steerability property is achieved using a set of basis filters that are rotated copies of one another. Therefore, a filter at any specific orientation can be obtained as a linear combination of these basis filters.

Following the steps to apply the SP to an input image: i) a grayscale image ($I(x, y)$) is decomposed into two sub-bands (low-pass and high-pass) by applying the filters H_0 , L_0 , respectively. ii) The low pass sub-band is decomposed into K directional band-pass components ($B_0, B_1, \dots, B_{K-1}$) and a residual low-pass sub-band (L_1). iii) This pyramidal architecture is constructed iteratively by down-sampling the low-pass sub-band by a factor of 2 along both spatial dimensions (x and y). Through this recursive framework, multi-scale directional information is extracted [29].

The basis functions of the steerable pyramid consist of directional derivative operators, i.e., derivative of Gaussian, parameterized by scale and orientation.

Let $L_0(r, \theta)$ and $H_0(r, \theta)$ the low-pass and high-pass filters in the frequency domain, respectively (Equation (33)):

$$\begin{aligned} L_0(r, \theta) &= L\left(\frac{r}{2}, \theta\right) / 2 \\ H_0(r, \theta) &= H\left(\frac{r}{2}, \theta\right), \end{aligned} \quad (33)$$

where r, θ are the polar frequency coordinates, and $L(r, \theta)$, $H(r, \theta)$ represents the low-pass and high-pass transfer functions (Equations (34) and (35)), where soft window functions, such as enhanced cosine functions, are used to prevent aliasing:

$$L(r, \theta) = \begin{cases} 2 \cos\left(\frac{\pi}{2} \log_2\left(\frac{4r}{\pi}\right)\right), & \frac{\pi}{4} < r < \frac{\pi}{2}, \\ 2, & r \leq \frac{\pi}{4}, \\ 0, & r \geq \frac{\pi}{2}, \end{cases} \quad (34)$$

$$H(r, \theta) = \begin{cases} \cos\left(\frac{\pi}{2} \log_2\left(\frac{2r}{\pi}\right)\right), & \frac{\pi}{4} < r < \frac{\pi}{2}, \\ 1, & r \geq \frac{\pi}{2}, \\ 0, & r \leq \frac{\pi}{4}. \end{cases} \quad (35)$$

Thus, the band-pass components $B_{\theta_k}(r, \theta) = H(r) \cdot G(\theta)$ are defined by a radial part $H(r)$ and angular part $G(\theta)$ for a base orientation at the angle θ_k (Equation (36)):

$$G_k(\theta) = \begin{cases} \alpha_k [\cos(\theta - \theta_k)], & |\theta - \theta_k| < \frac{\pi}{2} \\ 0, & \text{otherwise,} \end{cases} \quad (36)$$

where $\theta_k = \frac{\pi k}{K}$ and

$$\alpha_k = 2^{K-1} \frac{(K-1)!}{\sqrt{2K \cdot (K-1)}}. \quad (37)$$

Therefore, the extracted directional sub-bands $C_{s,\theta}(x, y)$ at scale s and orientation θ are defined by:

$$C_{s,\theta}(x, y) = \sum_{k=0}^{K-1} k_k(\theta) \left[L_{s-1}(x, y) \otimes B_K\left(\frac{x}{2^{s-1}}, \frac{y}{2^{s-1}}\right) \right], \quad (38)$$

where $L_{s-1}(x, y)$ is the low-pass response at the previous scale, $B_{\theta_k}(x, y)$ is the k -th directional basis filter at orientation θ_k , and $k_k(\theta)$ is the steering interpolation function defined by:

$$k_k(\theta) = \frac{1}{K} \left[1 + 2 \sum_{n=1}^{K-1} \cos \left(n \left(\theta - \frac{\pi k}{K} \right) \right) \right]. \quad (39)$$

The SP offers shift and rotation invariance and since any rotated filter can be synthesized as a linear combination of a small set of basis filters, it is highly utilized in optical flow estimation, stereo disparity analysis, and artifact-free image enhancement [11].

3.6. Spiking Neural Networks

In 1997, Maass introduced Spiking Neural Networks, regarded as the third generation of neural network models [12]. Since then, a wide range of SNNs-based methods have been proposed to process information using spikes generated by interconnected neurons, proving effective for HVS-based image processing [30], where SNNs-based approaches that emulate the HVS have provided superior edge detection performance compared with conventional gradient-based methods [14].

A typical SNNs-based architecture consists of a feedforward network of spiking neurons interconnected by multiple delayed synaptic terminals. Each neuron generates an action potential (spike) when its membrane potential reaches a threshold value (θ). The temporal relationship between input spikes and the membrane potential is described by the Spike Response Model (SRM), whose response functions can be configured to accurately represent the dynamics of diverse spiking neuron models [13].

Thus, a neuron j with a set of pre-synaptic neurons predecessors Γ_j receives a set of spikes with firing times t_k , $k \in \Gamma_j$. Each neuron produces at most one spikes during the simulation interval, firing when its membrane potential reaches a predefined threshold θ . The internal state variable $x_j(t)$ evolves according to the incoming spikes, whose influence is determined by the spike response function $\epsilon(t)$ scaled by the corresponding synaptic weight of the l -th terminal between neuron k and neuron j w_{kj}^l [13]:

$$x_j(t) = \sum_{k \in \Gamma_j} \sum_{l=1}^m w_{kj}^l \epsilon(t - t_k - d^l), \quad (40)$$

where m corresponds to the number of synaptic terminals per connection ($l = 1, \dots, m$), t_k is the firing time of the pre-synaptic neuron k , d^l represents the synaptic delay of the l -th terminal (defined as the time difference between the pre-synaptic spike and the moment the post-synaptic potential starts rising), and $\epsilon(t)$ is defined by Equation (41) (an α -function):

$$\epsilon(t) = \begin{cases} \frac{t}{\tau} \exp \left(1 - \frac{t}{\tau} \right), & t \geq 0 \\ 0, & t < 0, \end{cases} \quad (41)$$

where τ defines the membrane potential decay time constant, i.e., the rise and decay time of the post-synaptic potential, the variation in a neuron's membrane potential induced by an incoming pre-synaptic spike.

Unlike traditional artificial neuron, Spiking Neural Networks rely entirely on the precise timing between spikes to transfer information. This unique characteristic requires that any input data (usually in analog form) be explicitly converted into temporal patterns before it can be processed by the network. Typical encoding methods include rate coding, temporal coding, and population coding [13].

In visual applications, spike-timing encoding is the process of converting raw pixel intensities into discrete spike trains that a spiking neuron can process. Thus, the multidimensional pixel array, such as a raw image $I(x, y)$, must be mapped into a temporal space before being fed into the network.

On the other hand, to achieve this spatial-to-temporal transformation, Bohte et al. [31] proposed a population coding method that encodes an input variable using multiple overlapping Gaussian Receptive Fields (RF). In the context of image processing, these Gaussian RFs are utilized to translate continuous pixel values into precise firing times. The intensity range of the image data is first calculated, and each pixel is then encoded by a population of neurons that spans this entire data range. Specifically, for a coding interval defined by the pixel range $[I_{min}, I_{max}]$, a set of M Gaussian RF neurons is employed. The center $c_k(x_k, y_k)$ and the width σ_k of each individual RF neuron k are determined by Equations (42) and (43):

$$c_k = I_{min} + \left(\frac{2k-3}{2} \right) \left(\frac{I_{max} - I_{min}}{M-2} \right), \quad (42)$$

$$\sigma_k = \frac{1}{\gamma} \frac{I_{max} - I_{min}}{M-2}, \quad (43)$$

where γ is a scaling parameter that controls the overlap between adjacent receptive fields (typically set to a constant value, e.g., $\gamma = 1.5$).

For image processing (e.g., edge detection and clustering), SNNs can extract prominent contours and segment cells using local Hebbian learning and winner-take-all dynamics without requiring heavy training on large databases [13]. SNNs-based edge maps are sharper and more robust to noise and compression attacks, making them highly effective in digital image watermarking [14].

Thus, for an image $I(x, y)$ the analog response $\hat{I}_k(x, y)$ of the k -th Gaussian RF neuron response is:

$$\hat{I}_k(x, y) = I(x, y) \otimes \frac{1}{2\pi\sigma_k^2} \exp\left(-\frac{x_k^2 + y_k^2}{2\sigma_k^2}\right). \quad (44)$$

The analog activation response $\hat{I}_k(x, y)$ is then converted into an latency spike time $t_k(x, y)$ within a simulation window $[t_{min}, t_{max}]$ by:

$$t_k(x, y) = t_{min} + \lfloor (t_{max} - t_{min}) \cdot (1 - \hat{I}_k(x, y)) \rfloor. \quad (45)$$

Finally, the resulting spike signal $S_k(x, y, t)$ is defined as:

$$S_i(x, y, t) = \sum_i \delta(t - t_{k,i}(x, y)), \quad (46)$$

where $t_{k,i}(x, y)$ is the i -th spike time emitted by neuron k .

3.7. Dual-Tree Complex Wavelet Transform

The DT-CWT was proposed by Kingsbury et al. [15,16] to overcome the limitations of the standard Discrete Wavelet Transform (DWT), specifically its lack of shift invariance (sensitivity to small translations) and its poor directional selectivity in two or more dimensions.

Let $I(x, y)$ be a discrete two-dimensional image of size $N \times M$, where $x \in \{0, \dots, N-1\}$ and $y \in \{0, \dots, M-1\}$ denote the spatial row and column indices, respectively.

The DT-CWT decomposes the image $I(x, y)$ up to a maximum decomposition scale J . The forward transform maps the image into a set of complex scaling coefficients at the

coarsest scale J , and a set of complex wavelet coefficients across scales $j \in \{1, \dots, J\}$ and six spatial orientations $m \in \{1, \dots, 6\}$.

The complex approximation coefficients $A_J(k_x, k_y)$ at the final scale J are obtained by the inner product of the image with the conjugated 2D complex scaling function $\Phi_{c,J,k_x,k_y}(x, y)$:

$$A_J(k_x, k_y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} I(x, y) \Phi_{c,J,k_x,k_y}^*(x, y), \quad (47)$$

where k_x and k_y represent the spatial translation indices at the downsampled grid.

The complex directional detail coefficients $C_{j,m}(k_x, k_y)$ at scale j for the m -th orientation subband are formulated as:

$$C_{j,m}(k_x, k_y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} I(x, y) \psi_{c,m,j,k_x,k_y}^*(x, y), \quad (48)$$

where $*$ denotes the complex conjugate, and $\psi_{c,m,j,k_x,k_y}(x, y)$ represents the shifted and dilated 2D complex analytic wavelet function for the orientation angle $\theta_m \in \{\pm 15^\circ, \pm 45^\circ, \pm 75^\circ\}$.

Each complex coefficient can be explicitly written in terms of its real and imaginary parts, which are derived from four parallel real DWT filter banks:

$$C_{j,m}(k_x, k_y) = \text{Re}\{C_{j,m}(k_x, k_y)\} + \mathbf{j} \text{Im}\{C_{j,m}(k_x, k_y)\}, \quad (49)$$

where $\mathbf{j} = \sqrt{-1}$. This algebraic structure enables the direct calculation of the local magnitude and phase fields of the image.

The shift-invariance and true directional selectivity of the DT-CWT makes it suitable for image denoising, deblurring, and motion estimation, keeping reconstructed contours smooth and free of ringing artifacts [15,16].

3.8. Mimicking HVS Stages with Visual Models

To summarize the main differences between these bio-inspired mathematical visual models, Table 1 presents a comparison that includes their corresponding HVS stages and the receptive field structures they mimic.

Table 1. Comparative matrix of HVS-inspired visual models.

Model	HVS Stage	Receptive Field Structure
Retinex Model	Retina & Cerebral cortex	Center-surround opponent
DoG	Retinal ganglion cells	Circular center-surround
Gabor Filters	Striate cortex (simple cells V1)	Parallel excitatory/inhibitory
Hermite Transform	Primary visual cortex	Orthogonal Gaussian derivatives
Steerable Pyramid	Multi-resolution V1 geometry	Steerable derivatives
SNNs	Neural synapses	Integrate-and-fire dynamics
DT-CWT	Directional cortical channels	Analytic complex Gabor-like

3.9. Foundations and Computational Complexity of Bio-Inspired Mathematical Visual Models

Table 2 provides a comparison of the mathematical foundations of the seven bio-inspired visual models analyzed in this work, summarizing their mathematical decomposition processes and corresponding parameters.

Table 2. Comparative matrix of the mathematical foundations of the HVS-inspired visual models.

Model	Mathematical Foundations	Parameters
Retinex Model ^a	$R(x, y) = \log[I(x, y)] + \log[G(x, y, \sigma) \otimes I(x, y)]$	σ
DoG ^a	$D(x, y, \sigma) = \left(G(x, y, k\sigma) - G(x, y, \sigma) \right) \otimes I(x, y)$	k, σ
Gabor Filters	$\mathcal{I}(x, y) = \left[\exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \exp\left(i\left(2\pi\frac{x'}{\lambda} + \psi\right)\right) \right] \otimes I(x, y)$	$\lambda, \theta, \psi, \sigma, \gamma$
Hermite Transform ^b	$I_{m,n-m}(x, y) = D_{m,n-m}(x, y) \otimes I(x, y)(x, y)$	σ, N
Steerable Pyramid ^c	$C_{s,\theta}(x, y) = \sum_{k=0}^{K-1} k_k(\theta) \left[B_K\left(\frac{x}{2^{s-1}}, \frac{y}{2^{s-1}}\right) \otimes L_{s-1}(x, y) \right]$	S, K, θ
SNNs ^d	$\hat{I}_k(x, y) = \frac{1}{2\pi\sigma_k^2} \exp\left(-\frac{x_k^2 + y_k^2}{2\sigma_k^2}\right) \otimes I(x, y)$	$K, \gamma, M, \sigma_k, t_{min}, t_{max}, \tau$
DT-CWT	$A_J(k_x, k_y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} I(x, y) \Phi_{c,J,k_x,k_y}^*(x, y)$ $C_{j,m}(k_x, k_y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} I(x, y) \psi_{c,m,j,k_x,k_y}^*(x, y)$	J, θ_m

^a $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$

^b $D_{m,n-m}(x, y) = D_m D_{n-m}$
 $D_k(x) = \frac{(-1)^k}{\sqrt{2^k k!}} \frac{1}{\sigma\sqrt{\pi}} H_k\left(\frac{x}{\sigma}\right) \exp\left(-\frac{x^2}{\sigma^2}\right)$
 $H_k\left(\frac{x}{\sigma}\right) = (-1)^n \exp\left(-\frac{x^2}{\sigma^2}\right) \frac{d^n}{dx^n} \exp\left(-\frac{x^2}{\sigma^2}\right)$

^c $L_{s-1}(x, y) = L_0(2x, 2y) \otimes L_{s-2}(x, y)$
 $k_k(\theta) = \frac{1}{K} \left[1 + 2 \sum_{n=1}^{K-1} \cos\left(n\left(\theta - \frac{\pi k}{K}\right)\right) \right]$

^d $S_i(x, y, t) = \sum_i \delta(t - t_{k,i}(x, y))$
 $t_k(x, y) = t_{min} + \lfloor (t_{max} - t_{min}) \cdot (1 - \hat{I}_k(x, y)) \rfloor$

Regarding noise robustness, Table 3 shows a comparative analysis of the bio-inspired mathematical visual models, here it is shown that Gabor Filters, the Hermite transform, the Steerable Pyramid, and the DT-CWT exhibit a high level of noise robustness, whereas the Difference of Gaussians and SNNs have a medium level, and only the Retinex model has a low level.

Table 3. Comparative analysis of noise robustness across the bio-inspired mathematical visual models.

Model	Noise Robustness Level	Noise Handling
Retinex Model	Low	Amplifies high-frequency noise within dark or shadowed regions for local contrast enhancement
DoG	Medium	Smooths out high-frequency spatial noise, but its isotropic nature treats equally edges and noise
Gabor Filters	High	Suppresses all out-of-band noise due to its high localization in both the spatial and frequency domains.
Hermite Transform	High	Applies Gaussian smoothing prior to derivative extraction. Additionally, the Steered Hermite Transform extracts features by steering the Gaussian derivatives along the direction of maximum local energy
Steerable Pyramid	High	Isolates noise into specific frequency channels due to the multi-scale and multi-orientation sub-bands
SNNs	Medium	The intrinsic spike thresholding mechanism filters out low-amplitude noise, but high-frequency noise can disrupt spike timing and affect temporal encoding
DT-CWT	High	Allows precise noise separation due to shift-invariance and directional selectivity

Additionally, given the relevance of computational complexity in the analyzed bio-inspired mathematical visual models, a comparative runtime analysis was conducted to assess their real-time feasibility. a detailed description for each model is presented below. Table 4 summarizes the computational complexity across the different models.

Table 4. Computational complexity comparison across bio-inspired mathematical visual models.

Model	Lowest Computational Complexity
Retinex Model	$\mathcal{O}(P)$
Difference of Gaussians	$\mathcal{O}(P)$
Gabor Filters	$\mathcal{O}(F \cdot P \cdot \log P)$
Hermite Transform/Steered Hermite Transform	$\mathcal{O}(K \cdot P)$
Steerable Pyramid	$\mathcal{O}(F \cdot P \cdot \log P)$
Spiking Neural Networks	$\mathcal{O}(F \cdot P) + \mathcal{O}(N \cdot C \cdot S)$
Dual-Tree Complex Wavelet Transform	$\mathcal{O}(P)$

For an image $I(x, y)$ consisting of $P = M \times N$ pixels, the computational complexity of the Single-Scale Retinex Model using direct 2D spatial convolution is $\mathcal{O}(L^2 \cdot P)$, where $L \times L$ is the kernel size. Utilizing separable 1D filters reduces this complexity to $\mathcal{O}(L \cdot P)$, while recursive Gaussian filtering reduces it to $\mathcal{O}(P)$. Similarly, when using recursive filters for Gaussian smoothing, the computational complexity of the DoG model is $\mathcal{O}(P)$.

In the case of Gabor Filters, the computational complexity for a bank of F filters is $\mathcal{O}(F \cdot L^2 \cdot P)$ in the spatial domain, due to the non-separability of the filters. However, for a frequency-domain implementation, it is $\mathcal{O}(F \cdot P \cdot \log P)$.

On the other hand, the direct computational complexity of the Hermite Transform is $\mathcal{O}(K^2 \cdot L^2 \cdot P)$, where K is the maximum expansion order and L is the size of the Gaussian analysis window. However, this complexity can be reduced to $\mathcal{O}(K \cdot L \cdot P)$ using separable Gaussian-derivative filters, and further to $\mathcal{O}(K \cdot P)$ through discrete approximations (e.g., binomial filters and recursive operations).

Regarding the Steerable Pyramid, its direct implementation via spatial convolutions yields a computational complexity of $\mathcal{O}(F \cdot L^2 \cdot P)$, where F is the number of steerable filters of size $L \times L$. In the frequency domain, this becomes $\mathcal{O}(F \cdot P \cdot \log P)$, whereas using separable filters reduces it to $\mathcal{O}(F \cdot L \cdot P)$.

For the Spiking Neural Networks, the computational complexity depends on two stages: spatial coding using Gaussian Receptive Fields, and temporal coding. For the spatial coding stage, the computational complexity is $\mathcal{O}(F \cdot L^2 \cdot P)$ for a direct 2D convolution and $\mathcal{O}(F \cdot L \cdot P)$ when using 1D separable filters. Furthermore, this reduces to $\mathcal{O}(F \cdot P)$ if recursive filters are used. On the other hand, for the temporal coding stage, the computational complexity is $\mathcal{O}(N \cdot C \cdot S)$, where N is the number of neurons, C is the number of synapses per neuron, and S is the firing rate (i.e., the average number of spikes per neuron over time T). Thus, the total computational complexity is given by $\mathcal{O}(F \cdot P) + \mathcal{O}(N \cdot C \cdot S)$. Finally, for the DT-CWT, the computational complexity is $\mathcal{O}(P)$ due to the filter separability property, its optimized row-and-column implementation, as well as the down-sampling within the dual-tree structure.

As shown in Table 2, Gabor Filters, the Steerable Pyramid, and Spiking Neural Networks are the most elaborate bio-inspired visual models, due to their implementation steps and parameter count. In contrast, the Retinex Model, the Hermite Transform, and the DT-CWT are the least mathematically intricate models, in that order, requiring only a few parameters.

On the other hand, as shown in Table 4, models such as Retinex Model, DoG, and DT-CWT achieve the lowest computational complexity, but with limited image decomposition capabilities. Additionally, the Hermite Transform offers competitive computational

complexity while enabling complex image decomposition. In contrast, Gabor Filters and the Steerable Pyramid present higher computational complexity, whereas Spiking Neural Networks require the highest complexity.

3.10. Recent Developments of the Considered Bio-Inspired Mathematical Visual Models

In recent years, the visual models analyzed in this work have been applied to solve a wide range of image processing tasks. However, these models have recently shifted from standalone, static filtering frameworks toward adaptive, deep-learning-hybridized architectures. Furthermore, embedding bio-inspired mathematical visual models into modern learning frameworks yields superior interpretability, parameter efficiency, and structural robustness. Below, some recent developments in these visual models are highlighted.

Cai et al. [32] presented Retinexformer, a transformer network based on the Retinex theory that flattens the input image into tokens to perform self-attention operations along the channel dimension. Subsequently, it extracts relevant features through convolutional networks. In [33], Retinexformer+ was introduced as an advanced Retinex-based framework incorporating an illumination estimator alongside an illumination-fused U-Net. By leveraging multi-scale dilated convolutions, the illumination estimator extracts feature maps and models long-range pixel dependencies to enable accurate illumination adjustment. Xiao et al. [34] presented another enhanced Retinex deep learning architecture. It consists of a decomposition network that separates input images into reflection and illumination components through sequential convolutional layers, and an enhancement network that adjusts the illumination map to increase scene luminance, whereas a detail reconstruction module recovers structural fine points. In [35], Dutta et al. proposed a hybrid approach combining SNNs and the DoG filter for the diagnosis of intracranial tumors. Their architecture incorporates Spike-Timing-Dependent Plasticity and backpropagation within a network comprising multiple convolutional and pooling layers. Additionally, through an intensity-to-latency coding strategy, input images are converted into spike trains using a DoG filter. On the other hand, in [36], Jain et al. introduced a new quantum computing primitive that efficiently generates the discrete Hermite Transform and provides a quantum query advantage in property testing and learning. Wang and Kurihara [37] proposed an asymmetric complex steerable pyramid that decomposes blurred images into multi-scale frequency sub-bands to address motion deblurring. In [38], Yang et al. reported the Quarter-Sample Shift Dual-Tree Complex Wavelet Transform, which enhances multi-resolution processing by employing odd-length biorthogonal filters with a one-unit delay differential at the primary level, paired with even-length orthogonal filters exhibiting an approximate quarter-sample delay for subsequent levels. Thus, by using temporally reversed filter banks between dual trees, the constraint on coefficient symmetry is removed. This allows perfect reconstruction using orthogonal synthesis filters ensuring near shift-invariance and directional selectivity without computational redundancy.

4. Materials and Methods

This systematic review reported in this work was conducted in accordance with the PRISMA guidelines [39]. A PRISMA-guided Systematic Literature Review (SLR) is a rigorous and transparent secondary research methodology that synthesizes all available empirical evidence to answer a specific research question, following an international standard and a 4-phase flow diagram (Identification, Screening, Eligibility, and Inclusion) to ensure the quality and reproducibility of the process.

4.1. Protocol and Registration

The review protocol was registered on the Open Science Framework (OSF) on 22 September 2026 (Registration Identifier: <https://osf.io/7djfh>, accessed on 28 September 2026).

4.2. Research Questions

In this systematic review, the following research questions were posed:

- RQ1: To what extent have these visual models maintained relevance in recent real-world applications?
- RQ2: Which visual models are most frequently used in real-world applications?
- RQ3: What are the most frequent tasks addressed by each visual model in real-world applications?
- RQ4: Which visual models are most frequently preferred or dominant for each specific task?
- RQ5: What are the primary real-world applications for each visual model?

4.3. Search Strategy

In this review paper, we applied a comprehensive search strategy in Scopus, which is a widely recognized abstract and citation database. This search strategy was limited to documents written in English, as well as those in their final stage of publication. The following list outlines the specific terms used to search for the analyzed visual models:

1. Retinex Model
2. Difference of Gaussians
3. Gabor Filters
4. Hermite Transform and Steered Hermite Transform
5. Steerable Pyramid
6. Spiking Neural Networks
7. Dual-Tree Complex Wavelet Transform

Additionally, several terms related to image processing methods and analysis tasks were used to refine the dataset:

- image segmentation ,
- computer vision,
- image enhancement,
- watermarking,
- image analysis,
- image decomposition.

Besides, specific terms were applied to limiting the selection to works strictly applied to image-based problems:

- optical flow,
- security,
- monitoring,
- health,
- motion,
- magnification,
- cryptography,
- diagnosis,
- robotics,
- recognition.

On the other hand, specific exclusion terms (GAN*, Transformer*, audio) were applied to omit works utilizing modern deep learning architectures, such as Generative Adversarial Networks (GANs) and Vision Transformers (ViTs), as well as those focused on audio applications. Additionally, the search was refined to include only articles (AR), reviews (RE), and book chapters (CH), and in a first identification related works not corresponding to image processing methods or visual analysis tasks were eliminated.

Table 5 details the Boolean search strategy employed and presents the results generated by the database.

Table 5. Boolean search string and the results retrieved from the Scopus database.

Search String	Number of Results
AUTHKEY("Difference of Gaussian*" OR "Gabor filter*" OR "Retinex" OR "Hermite Transform*" OR "Steered Hermite Transform*" OR "Spiking Neural Network*" OR "Steerable Pyramid" OR "Dual-Tree Complex Wavelet Transform") AND AUTHKEY("image segmentation" OR "optical flow" OR "security" OR "monitoring" OR "health" OR "motion" OR "magnification" OR "computer vision" OR "watermarking" OR "cryptography" OR "diagnosis" OR "robotics" OR "image enhancement" OR "recognition" OR "image analysis" OR "image decomposition") AND NOT AUTHKEY("GAN*" OR "Transformer*" OR "audio") AND PUBYEAR >2019	452

* represents the wildcard operator.

Table 6 details the distribution of these works classified by both model and document type.

Table 6. First distribution of the works classified by both model and document type (Article = AR, Review = RE, Chapter = CH).

No.	Model	# Works	AR	RE	CH
1	Retinex Model	200	200	0	0
2	Difference of Gaussians	10	9	0	1
3	Gabor Filters	104	100	2	2
4	Hermite Transform/Steered Hermite Transform	11	11	0	0
5	Steerable Pyramid	10	10	0	0
6	Spiking Neural Networks	91	88	3	0
7	Dual-Tree Complex Wavelet Transform	26	26	0	0
Total		452	444	5	3

4.4. Eligibility Criteria

This study systematically review journal publications that apply one of the seven HVS models (GFs, HT/SHT, DoG, SNNs, RM, SP and DT-CWT) in image processing topics. The inclusion and exclusion criteria were defined to ensure that the review covers high-quality scientific studies relevant to the research questions. These eligibility criteria are presented in detail in Table 7. Since the search strategy was designed to include studies published between 2020 to 2026, these criteria are not repeated in the eligibility criteria. Eligibility criteria were divided into four categories in Table 7: scope, methods, publication type and language. Regarding scope, studies that performed application of image processing as image segmentation, computer vision, image enhancing, watermarking, image analysis and image decomposition were included without image modality restriction. However studies unrelated to this tasks are excluded. With respect to the Methods only the seven HVS

more easy to use are included and the models with prohibitive computational cost, lack of invertibility and high parametric sensitivity were excluded. To ensure the inclusion of high quality studies only research articles are included in the review excluding conferences proceedings and editorials.

Table 7. Eligibility criteria for selection of study materials for this review.

Criterion	Inclusion Criteria	Exclusion Criteria
Scope	Applications of image processing as image segmentation, computer vision, image enhancement, watermarking, image analysis, image decomposition	Applications that are not in image processing
Methods	HVS models: GFs, HT/SHT, DoG, SNNs, RM, SP and DT-CWT	HSV models as Fourier log-polar mapping, Naka-Rushton photoreceptors and Hopfield-based
Publication type	Research articles, chapter books	Conferences, editorials
Language	English	Other than English

4.5. Selection Protocol and Screening

To ensure rigorous work selection, a hierarchical three-stage screening protocol was executed:

1. Title screening: Preliminary filtering based on title relevance to select works incorporating at least one of the seven mathematical visual models.
2. Abstract and keyword screening: Detailed evaluation of abstracts and author keywords against pre-defined inclusion and exclusion criteria.
3. Full-text eligibility verification: Full-text analysis applied to studies with ambiguous titles or insufficient detail in the abstracts.

Both the selection and screening processes were manually performed by the two authors in a collaborative framework. The reviewed publications were partitioned between both researchers for primary data abstraction based on the predefined criteria, including model specifications, task categories, and application domains. Uncertainties or complex cases encountered during extraction were addressed via joint discussions to achieve full agreement. Automation tools were not employed in the data selection phase, and the screening relied exclusively on the published textual and graphical content.

4.6. Outcome Measures

The primary outcome domains for which data were sought were defined and categorized into three main levels:

- Visual model specifications: Biological inspiration stage, mathematical foundations, parameter count, computational complexity, and noise robustness.
- Bibliometric indicators: Distributions by visual model, document type, publication modality, and year, alongside citation counts, *h*-index, arithmetic mean, standard deviation, and adjusted Fisher-Pearson skewness coefficient.
- Task and real-world application mapping: Classification of publications by visual model across six primary image processing tasks, alongside the mapping of task preferences and real-world deployment domains per visual model.

Data processing, statistical computations, and visualization were executed using MATLAB (R2025b) equipped with the Statistics and Machine Learning Toolbox and the Image Processing Toolbox [40]. Additionally, some visualizations were performed using Python (v3.13.15) with the *numpy*, *matplotlib*, and *wordcloud* libraries inside the Google Colaboratory cloud environment [41].

All reported outcomes compatible with these domains were systematically extracted from each included study without pre-filtering, ensuring complete coverage across all selected publications.

4.7. Effect Measures

Given the qualitative nature of this systematic review, traditional comparative effect measures were not applicable. Instead, the synthesis and presentation of results relied on descriptive statistical measures and impact indicators. Specifically, categorical variables were synthesized using relative frequencies and percentage distributions across visual models, image processing tasks, and real-world applications domains. Bibliometric impact was evaluated using *h*-indices, citation counts, and were summarized using the arithmetic mean, standard deviation, and the adjusted Fisher-Pearson skewness coefficient to assess distribution symmetry.

4.8. Bias and Certainty Assessments

Due to the technical nature of this systematic literature review, formal statistical tests for reporting bias were not applicable. To minimize potential selection and reporting biases, a comprehensive and non-restrictive search strategy was executed across Scopus, serving as the primary indexing database. Furthermore, data extraction encompassed all published technical information, without filtering studies based on reported performance outcomes or model popularity.

On the other hand, formal certainty assessment frameworks were not applicable due to the technical and qualitative focus of this review. Instead, the reliability and validity of the body of evidence were ensured by selecting peer-reviewed publications indexed in primary databases, verifying technical specifications through collaborative dual-author extraction, and maintaining strict consistency across the defined classification schemes for visual models, image processing tasks, and real-world applications.

5. Results

5.1. Selection Process

The selection process for the works analyzed in this review is shown in Figure 1. First, the Scopus database was consulted using the Boolean search string presented in Table 5, yielding a total of 595 records. Then, the results were downloaded both in BibTeX format (file .bib) and Comma-Separated Values format (file .csv). The .bib file was imported to the JabRef, an open-source desktop bibliographic references manager, where several problems were corrected, for example, duplicated and non valid citation keys, and unsupported characters. Next, those works that not related to image processing or visual analysis tasks were removed, generating 452 records. Following, in the screening process 298 records lacking real-world applications were excluded, obtaining 153 final records to be included in this review. Finally, the selected records in the .csv file were saved in a spreadsheet file for your later analysis.

Representative works excluded during full-text screening, along with their primary rationale for exclusion, are summarized below:

- In [42], the authors present a Retinex-based decomposition as a two-player game to address non-uniform low-light image enhancement. In this work, the illumination and reflectance layers independently optimize their own utility functions. However, there is no direct real-world image processing application.
- In [43], a rotation- and scale-invariant approach for texture classification based on Gabor Filters is reported. The extracted features are evaluated on two public datasets.

This work was excluded because it does not demonstrate a direct real-world application.

- In [44], the authors present EfficientLIF-Net to minimize membrane voltage memory requirements in SNNs. This study was excluded as its primary scope is hardware-efficient network optimization rather than deploying real-world image processing applications.

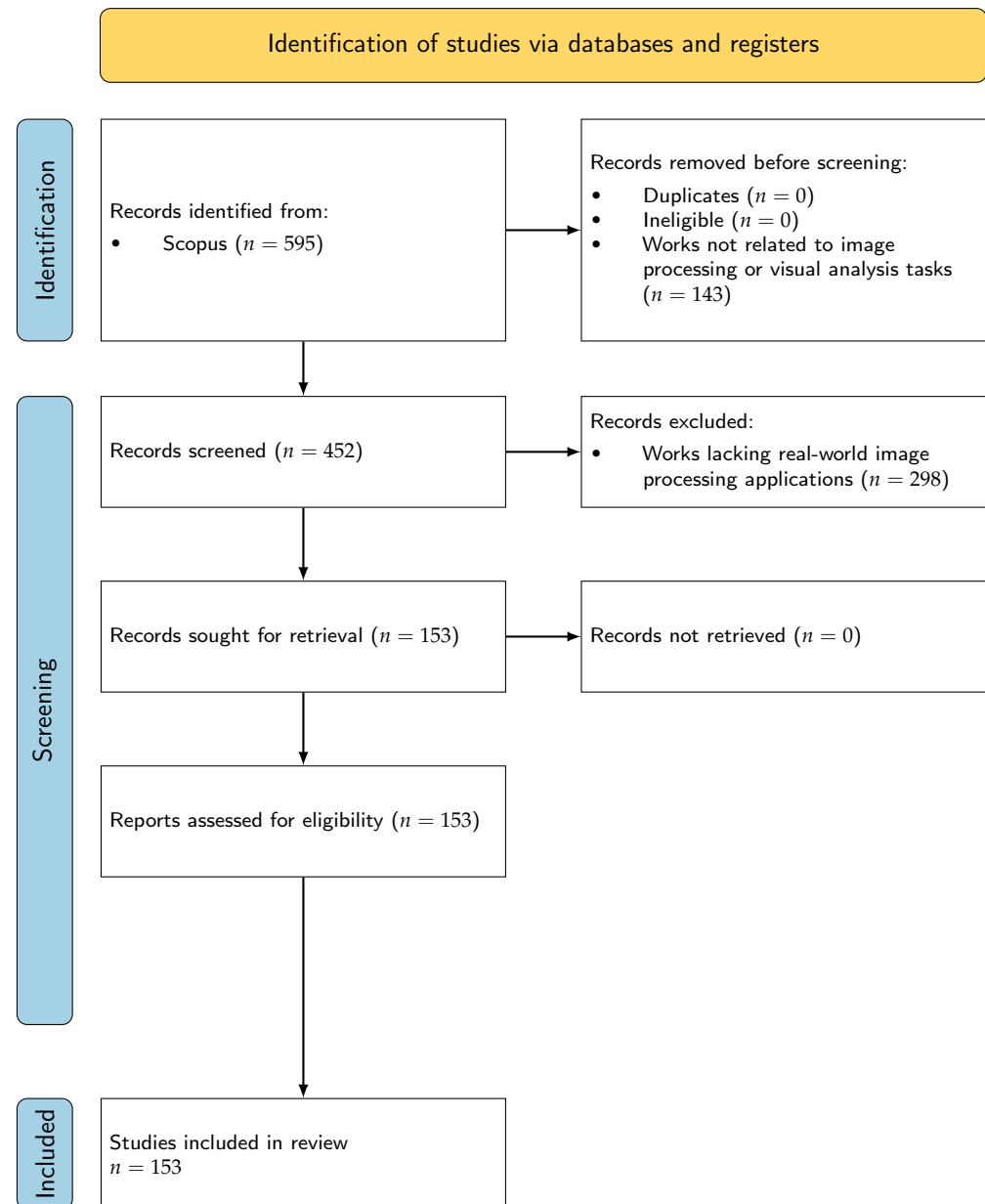


Figure 1. Flowchart strategy for the selection process.

5.2. Selected Works Statistics

Following screening, no sampling procedures were applied. This review included all eligible primary studies identified through the search and screening process that satisfied the predefined inclusion and exclusion criteria.

Table 8 shows the final distribution of the works classified by both model and document type. The initial 452 records (Table 6) was decreased to 153 records.

Table 8. Final distribution of the works classified by both model and document type (Article = AR, Review = RE, Chapter = CH).

No.	Model	# Works	AR	RE	CH
1	Retinex Model	31	31	0	0
2	Difference of Gaussians	9	9	0	0
3	Gabor Filters	38	37	0	1
4	Hermite Transform/Steered Hermite Transform	10	10	0	0
5	Steerable Pyramid	10	10	0	0
6	Spiking Neural Networks	30	30	0	0
7	Dual-Tree Complex Wavelet Transform	25	25	0	0
Total		153	152	0	1

The selected studies shown in Table 8 consisted of 153 journal articles (99.3%) and a book chapter (0.6%). Of the total articles, 53.6% (83 articles) were published under a traditional subscription model, while 45.8% (70 articles) were published as open access. Additionally, only a single chapter (0.6%) was published under a traditional subscription model (see Figure 2a).

Table 9 lists the journals that published more than one of the selected articles, detailing the number of articles per journal and their open access categories—Gold (Gd), Hybrid (H), Green (Gr), and Bronze (B)—with blank cells indicating a traditional subscription-based model. Additionally, Table A1 presents the complementary list of journals with a single publication, along with the single book chapter (CH).

Table 9. Number of articles per journal. Open Access Category (OAC): Gold (Gd), Hybrid (H), Green (Gr), Bronze (B).

Journal Name	Articles	OAC
Multimedia Tools and Applications	10	
Electronics (Switzerland)	6	Gd
Applied Sciences (Switzerland)	5	GdGr
Measurement: Journal of the International Measurement Confederation	4	
Frontiers in Neuroscience	3	GdGr
IEEE Access	3	GdGr
IEEE Sensors Journal	3	
Mathematics	3	GdGr
Algorithms	2	Gd
Applied Soft Computing	2	
Computer Methods and Programs in Biomedicine	2	
Expert Systems with Applications	2	
IAES International Journal of Artificial Intelligence	2	Gd
IEEE Geoscience and Remote Sensing Letters	2	
IEEE Transactions on Circuits and Systems for Video Technology	2	
Journal of Information Security and Applications	2	
Neural Networks	2	
Remote Sensing	2	GdGr

Additionally, Figure 2b presents the distribution of open access publications, breaking them down by their specific subcategories.

Table 10. Retinex Model applications.

Task	# Works	Applications	Works
Segmentation	1	Selective segmentation improvements in medical imaging	[45]
Watermarking/ Encryption	0	N/A	N/A
Motion Analysis and Robotics	5	Smoke-obscured navigation for firefighting robots; V-SLAM robotic localization in low-light construction zones, autonomous site monitoring under poor illuminance; sequence motion tracking via feature optimization; subterranean visual enhancement and hazard detection for coal mine exploration robots	[46–50]
Classification	4	Real-time image classification embedded with neuro-inspired color constancy; automated glaucoma detection/classification; deep brain tissue photoacoustic image processing and dental periapical lesion detection	[51–54]
Pattern Recognition	12	Industrial and infrastructure surface crack (tunnel lining, subaquatic tunnels, drill pipes, electrical equipment, coal transportation belts) and oil leakage spot detection; fire smoke recognition in nuclear power plants; drowsiness and night-time highway animal detection for vehicular safety; pedestrian re-identification in zero-shot/low-light environments and cervical precancerous lesion target enhancement	[55–66]
Image Enhancement	9	Underground mining visibility and drilling depth tracking; low-light remote sensing image clarification; crop color index stabilization for precision agricultural monitoring; non-destructive pipe weld radiography and selective laser melting quality inspection; emotional feature extraction from artistic images; and power transmission line ice monitoring and keypoint matching	[67–75]
Total	31		

Table 10 shows that the RM is mainly utilized for pattern recognition and image enhancement, followed closely by motion analysis and robotics, and classification tasks. In contrast, only one application falls under the segmentation category, and none are reported in the watermarking and encryption domains.

5.2.2. DoG-Based Applications

A total of nine works related to the Difference of Gaussians model were identified in the present review. Their distribution across the studied applications is detailed in Table 11.

Table 11. Difference of Gaussians applications.

Task	# Works	Applications	Works
Segmentation	2	Image segmentation in complex scenes; thermal facial expression segmentation	[76,77]
Watermarking/Encryption	0	N/A	N/A
Motion Analysis and Robotics	0	N/A	N/A
Classification	3	Structural health monitoring and damage detection; diabetic retinopathy diagnosis; real-time traffic sign recognition	[78–80]
Pattern Recognition	4	Robust face recognition amidst challenges; human action recognition (HAR); SVM-based face recognition under varying conditions; indoor human activity recognition via radar	[81–84]
Image Enhancement	0	N/A	N/A
Total	9		

As shown in Table 11, DoG applications are distributed across pattern recognition, classification, and segmentation.

5.2.3. Gabor Filter-Based Applications

A total of 38 works related to the Gabor Filters were identified. Table 12 presents the distribution of these works according to the specific tasks studied in this review, outlining the corresponding applications in which the Gabor Filters are employed.

Table 12. Gabor Filters applications.

Task	# Works	Applications	Works
Segmentation	8	Condition assessment of railroads; marine cold seep plume analysis; lumbar intervertebral disc modeling; crack detection in materials; retinal blood vessel isolation; grain counting in nanocrystals and residual yarn detection in textile bobbins	[85–92]
Watermarking/Encryption	0	N/A	N/A
Motion Analysis and Robotics	3	Vision-based structural displacement and vibration metrics; and motion processing segregation in biological higher visual areas	[93–95]
Classification	16	Fault diagnosis in rotating machinery; medical diagnosis (brain tumors, breast cancer, melanoma, diabetic retinopathy, lung nodules, Parkinson’s disease and endocervical gland hyperplasia); retinal fundus image classification; intelligent warehouse goods inventory; facial expression-based pain detection and classification for e-health systems; automated detection of Bemisia tabaci in yellow traps and seaweed species detection	[96–111]
Pattern Recognition	11	Biological identification (fish, honey plant pollen, tree images); age identification; sign language fingerspelling; muzzle prints for livestock; leather defect detection and steel strip texture recognition; automatic music chord recognition; substation equipment target identification and civil structural component detection using UAVs	[112–122]
Image Enhancement	0	N/A	N/A
Total	38		

Table 12 shows that GFs are primarily applied in classification tasks, followed by pattern recognition and segmentation applications. Finally, the literature includes only a few works in motion analysis and robotics applications, while no publications were identified within the watermarking and encryption fields, and image enhancement.

5.2.4. HT- and SHT-Based Applications

Regarding the Hermite Transform and Steered Hermite Transform, a total of ten works were identified in this review. Table 13 shows the distribution of these publications across the applications addressed in this study.

Furthermore, as indicated in Table 13, the HT/SHT model exhibits a well-balanced distribution across the investigated applications. Thus, the HT/SHT model is primarily applied in watermarking and encryption fields, followed by motion analysis and robotics. Lastly, this model is utilized for classification and pattern recognition applications, showing limited application in segmentation and image enhancement tasks.

Table 13. Hermite Transform/Steered Hermite Transform applications.

Task	# Works	Applications	Works
Segmentation	0	N/A	N/A
Watermarking/ Encryption	6	Authentication of fundus images in computer-aided diagnosis of retinopathy; grayscale image copyright protection; secure dual-image embedding; color image watermarking	[123–128]
Motion Analysis and Robotics	3	3D optical flow estimation in left ventricle CT sequences; non-contact breathing/respiratory rate estimation tracking chest movements	[129–131]
Classification	1	Peripheral oxygen saturation (SpO_2) estimation	[132]
Pattern Recognition	0	N/A	N/A
Image Enhancement	0	N/A	N/A
Total	10		

5.2.5. Steerable Pyramid-Based Applications

A total of ten works related to the Steerable Pyramid model were identified in the present review. Their distribution across the studied applications is detailed in Table 14.

Table 14. Steerable Pyramid applications.

Task	# Works	Applications	Works
Segmentation	0	N/A	N/A
Watermarking/ Encryption	1	E-health cloud secured login authentication using biometric face descriptors	[133]
Motion Analysis and Robotics	6	Time-domain vibration measurement; vision-based structural displacement tracking under optical turbulence; rotating machinery fault diagnostics; optimal scale level selection for subpixel estimation; pulsatile brain and CSF movement tracking	[134–139]
Classification	2	Multi-language handwritten character classification (Kannada, Arabic, English); celiac disease detection and villous atrophy classification from biopsy images	[140,141]
Pattern Recognition	1	Texture-based iris recognition	[142]
Image Enhancement	0	N/A	N/A
Total	10		

As shown in Table 14, SP model exhibits a well-balanced distribution across the investigated applications. The SP applications are primarily distributed across motion analysis and robotics and classification, showing limited application in segmentation, pattern recognition, and image enhancement tasks.

5.2.6. SNN-Based Applications

The literature search yielded 30 publications focusing on Spiking Neural Networks. Their distribution across the studied tasks is detailed in Table 15.

Table 15 highlights the predominant application of SNNs across classification, segmentation, and motion analysis and robotics, followed by image enhancement, watermarking and encryption, and pattern recognition.

Table 15. Spiking Neural Networks applications

Task	# Works	Applications	Works
Segmentation	6	Brain extracellular space (ECS) in cryo-EM data; human hippocampi MRI segmentation; high-fidelity medical attention mapping; early-stage agricultural Sclerotinia detection; multi-threshold Spiking-UNet processing; and retinopathy area extraction	[143–148]
Watermarking/ Encryption	2	Edge-directed digital image watermarking and privacy-preserving homomorphic encryption frameworks for SNNs architectures	[14,149]
Motion Analysis and Robotics	5	High-speed optical flow learning from spike streams; 3-point direction-selective Time-Difference Encoders; hardware accelerators (ASNA-Flow); long-term temporal human action aggregation; and dense automotive optical flow estimation	[150–154]
Classification	11	Satellite remote sensing object recognition; SAR target recognition; medical dermoscopy skin cancer categorization; FMCW radar gesture classification; neuromorphic pedestrian/vehicle detection; ambient assisted living eldercare movement activity tracking; LCD handwritten digit recognition; event-driven sign language processing; and wavelet-based disease categorization	[155–165]
Pattern Recognition	2	Content-based Image Retrieval (CBIR) through edge detection; and computer-aided diabetic retinopathy grading from fundus photography	[166,167]
Image Enhancement	4	Artifact suppression in complex generative underwater networks (LAMSN); dual-stream hybrid event deblurring (EDHnet); and early visual system biological feature codebooks	[168–171]
Total	30		

5.2.7. DT-CWT Applications

Regarding the DT-CWT, 25 relevant studies were retrieved and analyzed. Table 16 categorizes these works based on the specific tasks under review, while also illustrating the respective application fields where this approach is implemented.

Table 16. Dual-Tree Complex Wavelet Transform applications.

Task	# Works	Applications	Works
Segmentation	1	Medical diagnostics in brain tumor segmentation	[172]
Watermarking/ Encryption	16	Copyright protection; medical image security; transmission channel defense; social media content authentication; camcording resistance and digital tamper proofing	[173–188]
Motion Analysis and Robotics	0	N/A	N/A
Classification	1	Real-time driver drowsiness monitoring and risk mitigation	[189]
Pattern Recognition	5	Radar target identification; illumination-invariant facial verification and kinship recognition a by disease severity scale for Soybean Mosaic Virus	[190–194]
Image Enhancement	2	Restoration of low-light images and quality enhancement of clinical CT scans	[195,196]
Total	25		

Table 16 suggests that the DT-CWT is primarily used in the watermarking and encryption domains. Additionally, the DT-CWT is applied, to a lesser extent, in pattern recognition

tasks and image enhancement. Finally, the DT-CWT is rarely used in segmentation and classification fields, and it is entirely absent from motion and robotics applications.

5.3. Data Synthesis

This section presents the responses to the research questions posed in this systematic review, which aims to characterize the temporal evolution, task-specific specialization, and the practical deployment of bio-inspired mathematical visual models across contemporary image processing tasks..

5.3.1. RQ1: To What Extent Have These Visual Models Maintained Relevance in Recent Real-World Applications?

Figure 4 shows the distribution of the selected publications by year and visual model, including the arithmetic mean for each model as a horizontal line. Additionally, Figure 5 presents a heatmap showing visual model usage over the time.

As shown Figures 4 and 5, the Retinex Model has shown an increasing trend since 2023, while the Difference of Gaussians has remained relatively stable, experiencing a slight increase in 2024 followed by a sharp decline in 2026. Regarding the Hermite and Steered Hermite transforms, publications have appeared consistently from 2020 to 2026, despite declines in 2021 and 2026. A similar trend was observed for the Steerable Pyramid model, which saw decreases in 2020 and 2023. Finally, Spiking Neural Networks and the Dual-Tree Complex Wavelet Transform both exhibited a trend resembling a bell-shaped curve, reaching their peak presence in 2025 and 2021, respectively.

Additionally, Table 17 shows the arithmetic mean, the standard deviation, and the adjusted Fisher-Pearson skewness coefficient G_1 (see Equation (50)) for each visual model over time.

$$G_1 = \frac{n}{(n-1)(n-2)} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{s} \right)^3, \quad (50)$$

where, for each visual model, n represents the number of publications, x_i corresponds to the number of publications in year i , $\bar{x}$ is the arithmetic mean, and s is the standard deviation.

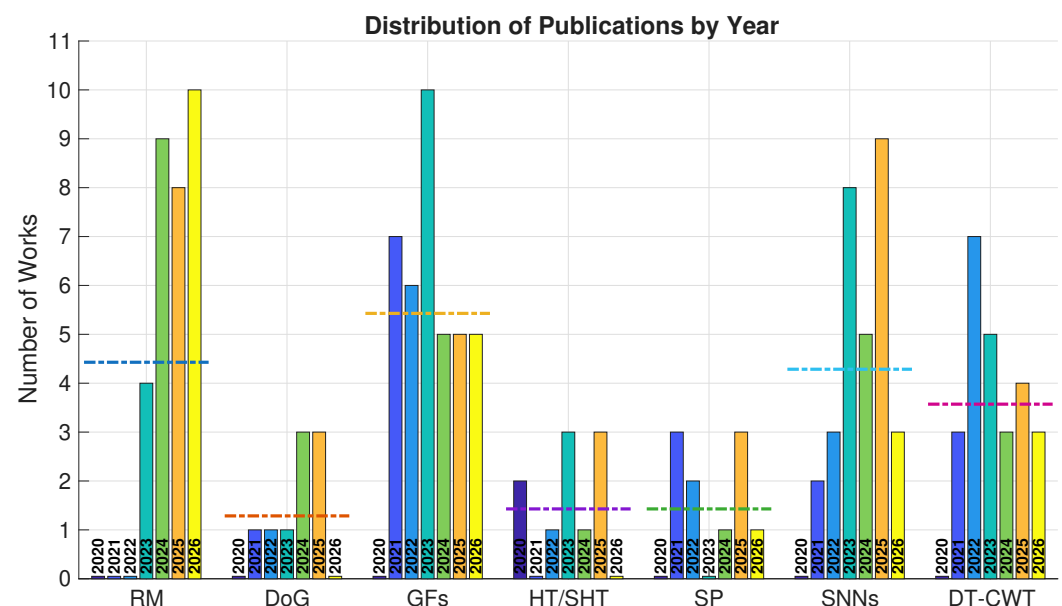


Figure 4. Distribution of publications categorized by publication year and visual model. Retinex Model (RM), Difference of Gaussians (DoG), Gabor Filters (GFs), Hermite Transform and Steered Hermite Transform (HT/SHT), Steerable Pyramid (SP), Spiking Neural Networks (SNNs), and Dual-Tree Complex Wavelet Transform (DT-CWT). Horizontal lines represent the arithmetic mean of the number of publications for each visual model over the analysis period.

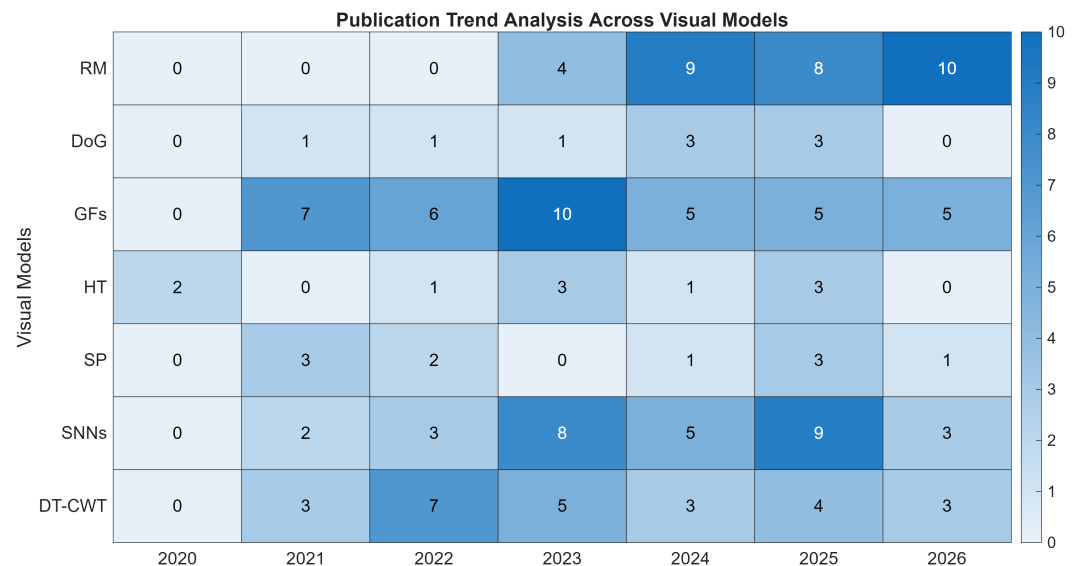


Figure 5. Heatmap illustrating the distribution of publications categorized by publication year and visual model. Retinex Model (RM), Difference of Gaussians (DoG), Gabor Filters (GFs), Hermite Transform and Steered Hermite Transform (HT/SHT), Steerable Pyramid (SP), Spiking Neural Networks (SNNs), and Dual-Tree Complex Wavelet Transform (DT-CWT).

Table 17. Descriptive statistics for each visual model over time.

Model	$\bar{x}$	s	G_1
Retinex Model	4.428	4.540	0.133
Difference of Gaussians	1.285	1.253	0.681
Gabor Filters	5.428	2.992	−0.528
Hermite Transform/Steered Hermite Transform	1.428	1.272	0.221
Steerable Pyramid	1.428	1.272	0.221
Spiking Neural Networks	4.285	3.251	0.221
Dual-Tree Complex Wavelet Transform	3.571	2.149	0.417

Figure 6 shows the distribution of citation counts across publications, with at least one citation, for the selected models. Additionally, Table 18 shows the h -index for each visual model across its publication set ($P = \{p_1, p_2, \dots, p_N\}$), defined as the maximum integer h such that h publications have at least h citations each:

$$h\text{-index} = \max\{i \in \mathbb{N} \mid C_i \geq i\} \quad (51)$$

where C_i is the citation count of the i -th publication when ranked in descending order of citations.

Table 18. h -index and citation values by visual model.

Model	# Works	Uncited	At Least 1 Citation	h -Index
Retinex Model	31	13 (41.9 %)	18 (58.1 %)	8
Difference of Gaussians	9	3 (33.3 %)	6 (66.6 %)	4
Gabor Filters	38	8 (21 %)	30 (79 %)	9
Hermite Transform/Steered Hermite Transform	10	3 (30 %)	7 (70 %)	6
Steerable Pyramid	10	1 (10 %)	9 (90 %)	5
Spiking Neural Networks	30	3 (10 %)	27 (90 %)	8
Dual-Tree Complex Wavelet Transform	25	2 (8 %)	23 (92 %)	10

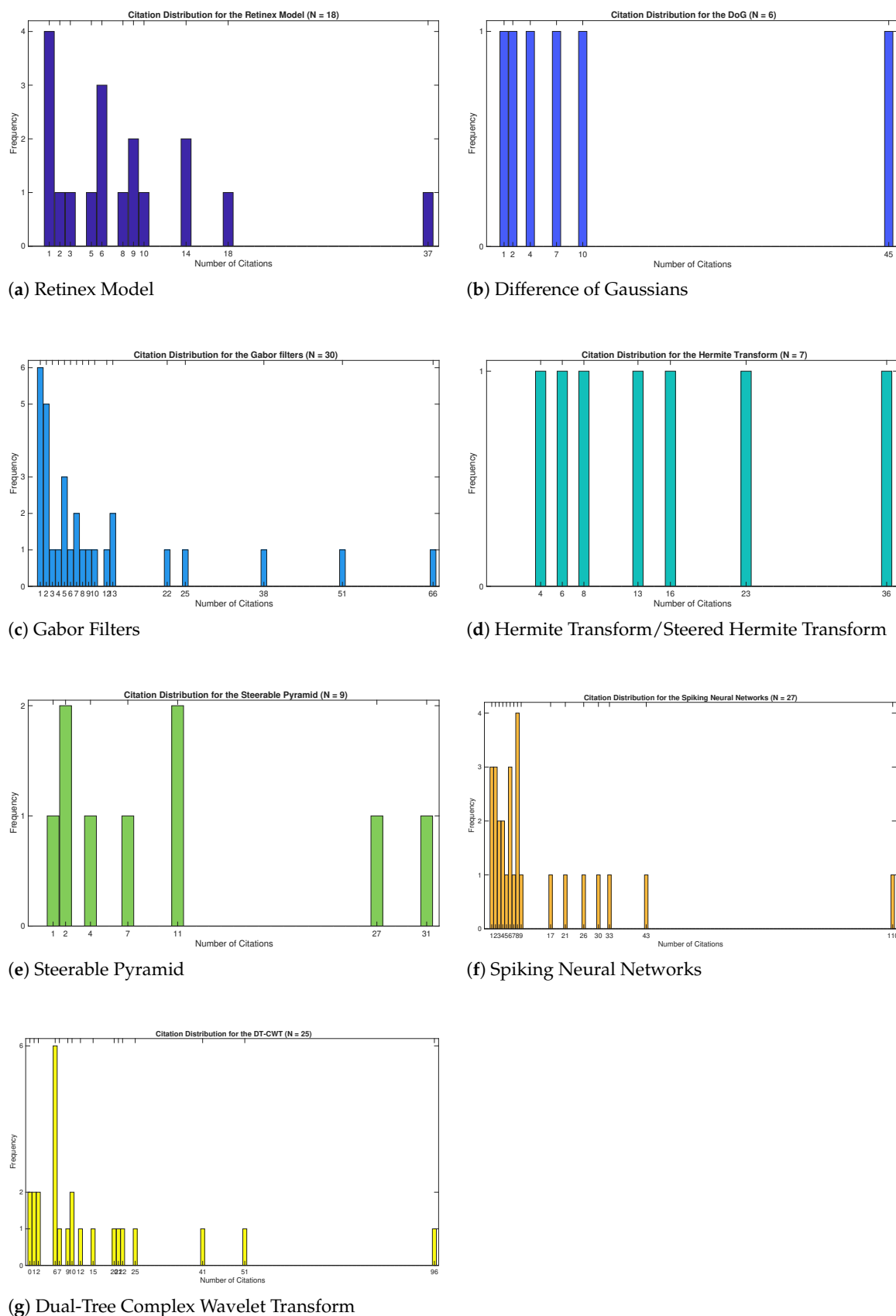


Figure 6. Distribution of citation counts of the works for the visual models.

Figure 4 and Table 17 show that the Retinex Model and SNNs are the visual models with the most recent temporal presence. Both exhibit a high arithmetic mean (4.428 and

4.285, respectively) but also high volatility, as indicated by their standard deviations (4.540 and 3.251). On the other hand, DoG, HT/SHT, and SP are visual models whose year-by-year production is unpredictable, with arithmetic means very similar to their standard deviations, and characterized by some years with higher publication volumes alongside others with lower values or no publications at all. In the case of the GFs and DT-CWT models, they can be characterized as robust yet dynamic. That is, they feature a high volume of scientific production ($\bar{x}$ of 5.418 and 3.571) paired with moderate fluctuations (s of 2.992 and 2.149), indicating a sustained interest from the scientific community.

On the other hand, regarding adjusted Fisher-Pearson skewness coefficient, Retinex Model, GFs, HT/SHT, SP, and SNNs present a negligible asymmetry with a stable annual production ($|G_1| \leq 0.5$). DoG and DT-CWT shows a moderate asymmetry ($|G_1|$ of 0.681 and 0.417), with a few years of high but very intense production, years 2024 and 2025 for DoG model; and years 2021 and 2022 for DT-CWT model.

Finally, Figure 6 and Table 18 show that the least-cited works are those using the Retinex Model (41.9%), followed by the DoG model (33.3%). In contrast, publications using DT-CWT, SNNs, and Steerable Pyramids show the highest percentage of works with at least one citation. Regarding the h -index, publications using DT-CWT, Gabor Filters, and SNNs, with an h -index of 10, 9 and 8, respectively, confirm the productivity and consistent impact of these models into the field of application. Although works using the Retinex Model have a lower overall citation rate, they achieve an h -index of 8, indicating that those works that are cited carry a high impact. The Hermite Transform represents a balanced model, exhibiting a low uncited rate while achieving an acceptable h -index of 6.

5.3.2. RQ2: Which Visual Models Are Most Frequently Used in Real-World Applications?

Figure 7 shows the distribution of visual models across real-world applications within the selected publications.

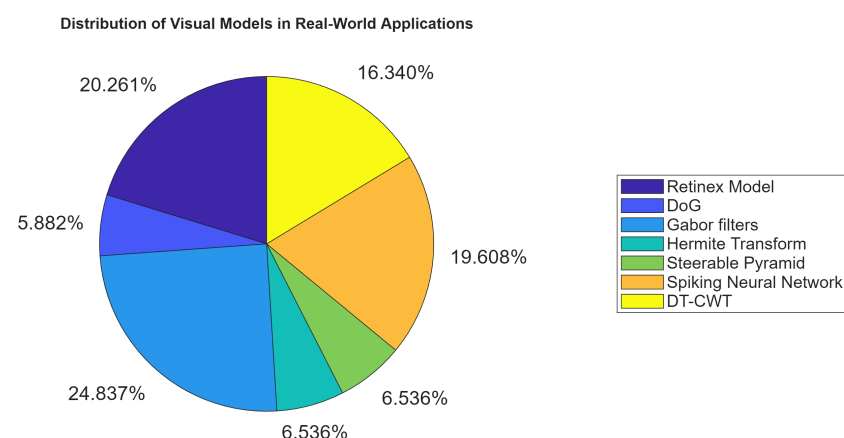


Figure 7. Visual models most frequently used in real-world applications.

According to Figure 7 and Table 8, Gabor Filters (24.8%) represent the predominant model deployed in real-world applications. The Retinex model and SNNs follow closely, representing 20.3% and 19.6% of the publications, respectively. On the other hand, DT-CWT stands at 16.3%. Finally, HT/SHT and the Steerable Pyramid each represent 6.5%, with DoG capturing the remaining 5.9%.

5.3.3. RQ3: What Are the Most Frequent Tasks Addressed by Each Visual Model in Real-World Applications?

Figure 8 shows the distribution of applications by visual model in the selected publications, where the percentages shown correspond to each specific visual model; thus, the

sum of all applications for a given model equals 100%. Additionally, Figure 9 presents a heatmap showing visual model usage across real-world applications.

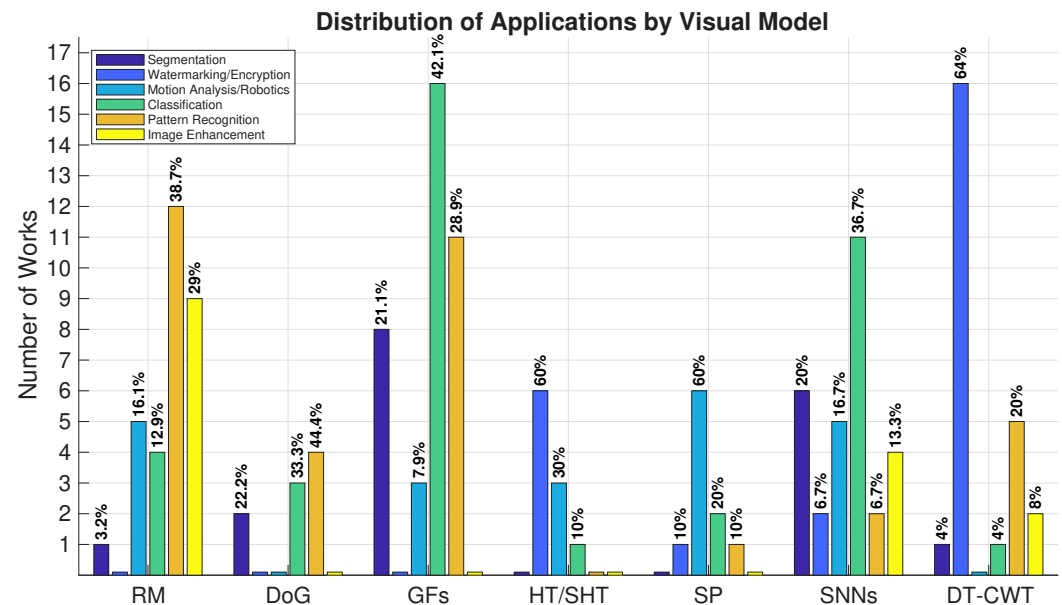


Figure 8. Distribution of applications by visual model in the selected publications. Retinex Model (RM), Difference of Gaussians (DoG), Gabor Filters (GFs), Hermite Transform and Steered Hermite Transform (HT/SHT), Steerable Pyramid (SP), Spiking Neural Networks (SNNs), and Dual-Tree Complex Wavelet Transform (DT-CWT).

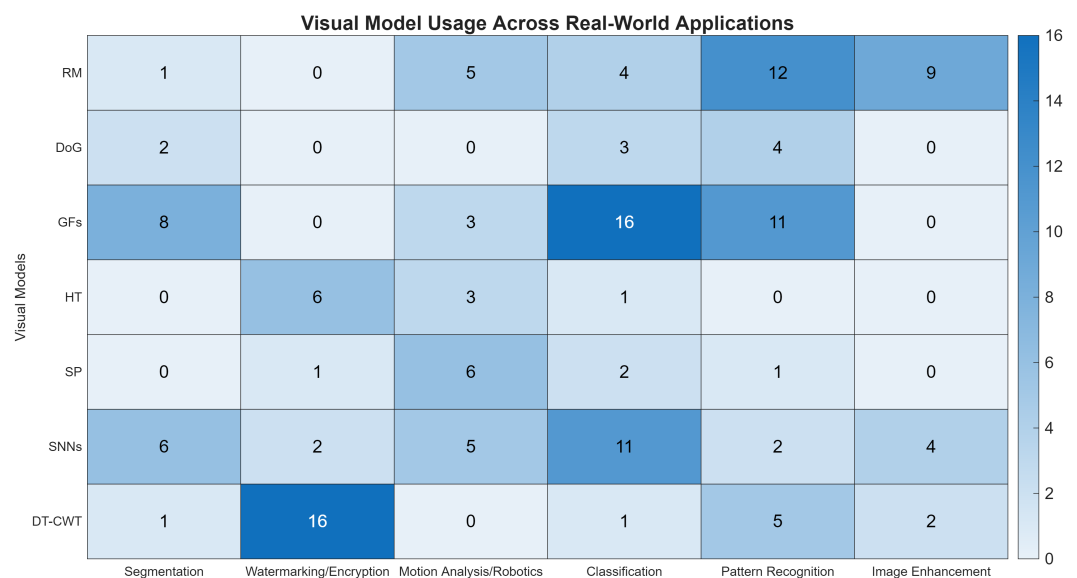


Figure 9. Heatmap illustrating the distribution of visual model usage across real-world applications. Retinex Model (RM), Difference of Gaussians (DoG), Gabor Filters (GFs), Hermite Transform and Steered Hermite Transform (HT/SHT), Steerable Pyramid (SP), Spiking Neural Networks (SNNs), and Dual-Tree Complex Wavelet Transform (DT-CWT).

According to Figures 8 and 9, the Retinex Model is mainly applied to pattern recognition (38.7%) and image enhancement (29%) tasks. The DoG model is predominantly applied to pattern recognition (44.4%), classification (33.3%) and segmentation (22.2%). Meanwhile, Gabor Filters are most frequently utilized across three tasks: classification (42.1%), pattern recognition (28.9%), and segmentation (21.1%).

On the other hand, the HT/SHT model covers watermarking and encryption (60%) as well as motion analysis and robotics (30%). Furthermore, SP is mainly applied to motion analysis and robotics (60%). Additionally, SNNs applications are distributed across several tasks, led by classification (36.7%), segmentation (20%), and motion analysis and robotics (16.7%). Finally, the DT-CWT model is predominantly applied to watermarking and encryption applications (64%), followed by pattern recognition tasks (20%).

As a key real-world application, we consider the medical field. Thus, out of the 153 works analyzed in this study (Table 8), 33 studies (21.5%) process medical images for diagnostic support or involve e-health applications. Table 19 compares the bio-inspired visual models used for processing medical images. Within the literature for each model, 50% of works on the Hermite Transform are applied to the medical domain, followed by Gabor Filters (31.5%), Steerable Pyramids (30%), and Spiking Neural Networks (23.3%). In contrast, the visual models least used for medical applications are the DoG (11.1%), the Retinex Model (9.6%), and the DT-CWT (8%).

Table 19. Comparative analysis of visual models in medical image processing

Model	# Works	Applications
Retinex Model	3 of 31 (9.6%)	Medical images segmentation [45], glaucoma detection [52] and classification, cervical precancerous lesion detection [66]
Difference of Gaussians	1 of 9 (11.1%)	Diabetic retinopathy lesions classification [79]
Gabor Filters	12 of 38 (31.5%)	Breast cancer detection [98,100], lumbar intervertebral disc segmentation [88], melanoma Classification [101], Diabetic retinopathy level grading [103], lung nodule classification [104], retinal blood vessels segmentation [90], automated glaucoma diagnosis [107], lobular endocervical glandular hyperplasia classification [108], brain tumor detection [109], retinal vasculature segmentation [92], Parkinson's disease diagnosis [110]
Hermite Transform/Steered Hermite Transform	5 of 10 (50%)	Left ventricle motion estimation [129], fundus image watermarking [123], contactless respiratory rate estimation [130,131], non-contact oxygen saturation estimation [132]
Steerable Pyramid	3 of 10 (30%)	secure face-based e-health authentication in cloud environments [133], celiac disease detection [141], 3D amplified MRI [138]
Spiking Neural Networks	7 of 30 (23.3%)	Brain segmentation [143,144], medical image classification and segmentation [145,157,164], diabetic retinopathy grading [148,167]
Dual-Tree Complex Wavelet Transform	2 of 25 (8%)	Brain tumor segmentation [172], CT image enhancement [196]

5.3.4. RQ4: Which Visual Models Are Most Frequently Preferred or Dominant for Each Specific Task?

Figure 10 illustrates the distribution of the reviewed publications by specific task alongside the visual models used.

Consequently, within the segmentation task, GFs and SNNs collectively account for 77.7% of the publications (representing 44.4% and 33.3%, respectively). In watermarking and encryption applications, DT-CWT accounts for 66.7% of the publications, followed by HT/SHT at 20.8%. In motion analysis and robotics applications, SP represents 27.3% of the implementations, followed by RM and SNNs at 22.7% each. Furthermore, HT/SHT and GFs represent 13.6% of the publications respectively. For classification tasks, GFs represent the dominant model, accounting for 42.1% of the publications, followed by SNNs with 28.9%. For pattern recognition applications, the publications are primarily distributed between RM (33.3%) and GFs (30.6%). Finally, image enhancement tasks are dominated

by RM (60%), followed by SNNs and DT-CWT models, representing 26.7% and 13.3%, respectively.

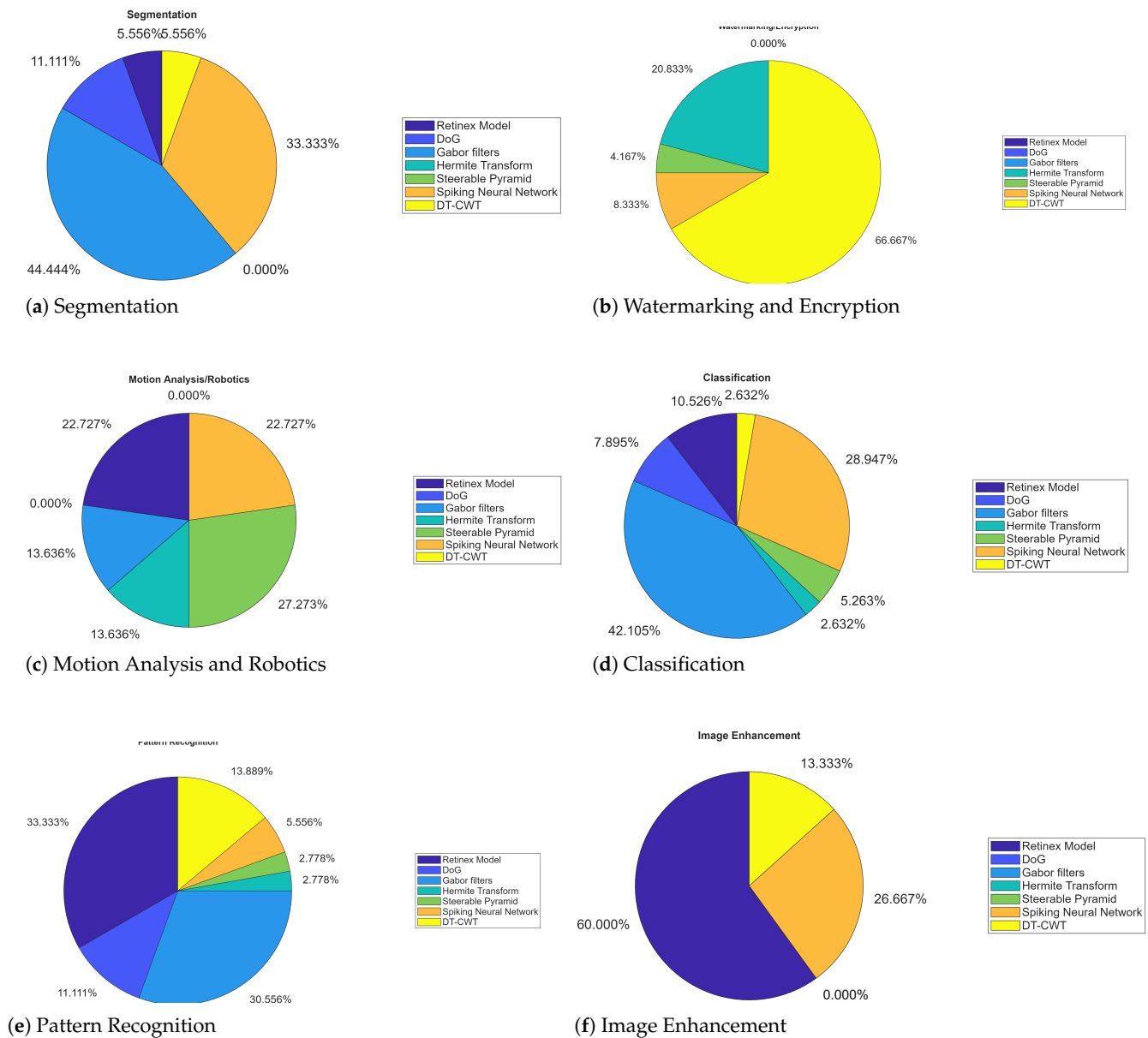
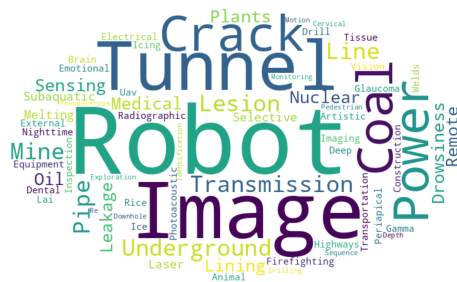


Figure 10. Distribution of the selected publications by specific task and visual model.

5.3.5. RQ5: What Are the Primary Real-World Applications for Each Visual Model?

Figure 11 presents the word clouds generated from the keywords of the selected articles based on visual models.

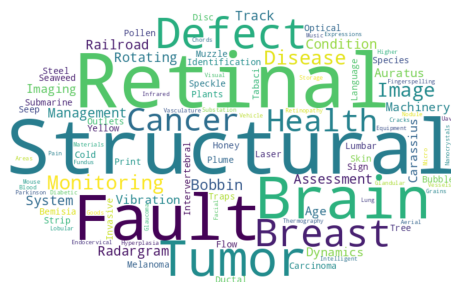
As shown in Figure 11a, robotics, tunnel crack, coal, driver drowsiness, pipe, mine, and underground are the most principal keywords in the publications utilizing the Retinex Model. These terms reflect two main application domains: hazardous infrastructure inspection and intelligent transportation safety. This is because the RM stands out for its exceptional performance in both color constancy and illumination compensation, which are crucial for challenging environments characterized by low-light, uneven, or degraded visual conditions.



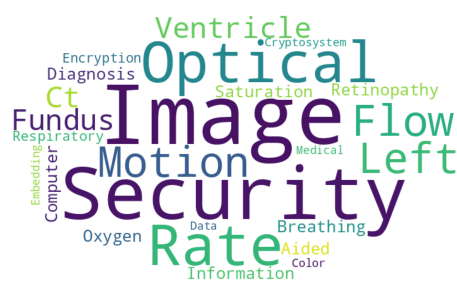
(a) Retinex Model



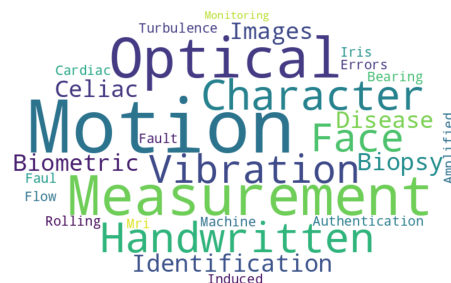
(b) Difference of Gaussians



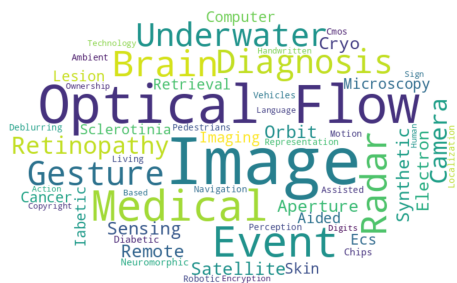
(c) Gabor Filters



(d) The Hermite Transform/Steered Hermite Transform



(e) Steerable Pyramid



(f) Spiking Neural Networks



(g) Dual-Tree Complex Wavelet Transform

Figure 11. Word cloud generated from the keywords of selected articles targeting (a) the Retinex Model, (b) Difference of Gaussians, (c) Gabor Filters, (d) the Hermite Transform/Steered Hermite Transform, (e) the Steerable Pyramid, (f) Spiking Neural Networks, and (g) Dual-Tree Complex Wavelet Transform.

As illustrated in Figure 11b, the most prominent keywords appearing in the selected publications for DoG include face, human, health structural, human action, monitoring, face, and diabetic retinopathy. Thus, an analysis keywords refers that the literature is heavily concentrated in structural healthcare monitoring, medical diagnosis, human action, and facial monitoring. This is because the DoG model enables robust feature extraction, which is utilized for object tracking and identification, as well as for detecting specific markers of particular diseases.

Furthermore, an analysis of the GFs keywords (Figure 11c) reveals that the terms structural, health monitoring, facial, and retinal were highly prevalent. Additionally, related keywords such as cancer, breast, tumors, health, fault, machinery, railroad, and vibration were identified. This highlights that Gabor Filters are highly versatile, covering two application domains: industrial structural health monitoring and medical diagnosis. In industrial domain, this model is applied to machinery fault diagnosis and structural infrastructure monitoring. Meanwhile, in biomedical applications, it is frequently utilized for human health monitoring and specific diagnostic tasks targeting regions such as the breast and retina.

In contrast, the keyword analysis for the HT/SHT model (Figure 11d) revealed prominent terms such as motion, security/encryption, optical flow, breathing rate/oxygen saturation, fundus image, and diagnosis. These keywords indicate that this model is primarily applied across motion estimation and tracking, data security (watermarking), and medical diagnosis using fundus images, as well as vital signs monitoring, including respiratory rates and blood oxygen saturation. In particular, there are specific applications rely on image synthesis, which is highly relevant due to the perfect reconstruction property of the HT/SHT model.

On the other hand, Figure 11e highlights prominent keywords such as motion, vibration, measurement, handwritten, identification, turbulence, biometric, biopsy and disease. These terms indicate a distribution of the literature across diverse fields ranging from structural mechanics monitoring and biometric identification to medical diagnostics. This versatility is possible thanks to the model's multi-scale directional filtering capabilities, which are also found in frameworks like the HT/SHT model.

In the case of SNNs (Figure 11f), the analysis of the word cloud for SNNs models reveals prominent keywords such as: optical flow, event, gesture, retinopathy, brain, diagnosis, retrieval, encryption, and underwater. These keywords indicate that the model is actively used for motion estimation, event analysis, gesture recognition, medical diagnostics, and underwater imaging. Therefore, these applications demonstrate that SNNs are highly advantageous in scenarios where temporal information is critical.

Finally, as shown in Figure 11g, copyright, protection, security, identification, face, authentication, monitoring, drowsiness, tumor, and brain are the principal keywords in publications utilizing the DT-CWT. This indicated that three main domains concentrate the applications of DT-CWT model: information security, biometrics identification and medical diagnosis. The directional selectivity and exact image reconstruction makes it model suitable for copyright protection (watermarking) and authentication systems. Additionally, there are interesting applications such as detecting driver drowsiness and brain tumor segmentation.

5.4. Heterogeneity Handling

In this review, potential causes of heterogeneity in research impact and publication trends were evaluated through visual model subgroup stratification and distribution analysis. Specifically, variations across visual models were examined in relation to publication year and temporal adoption. To quantify impact heterogeneity, descriptive statistics, in-

cluding the arithmetic mean, standard deviation, *h*-index, and the adjusted Fisher-Pearson skewness coefficient, were computed across visual model categories. As shown in Table 17, the positive skewness observed across citation distributions confirms significant impact heterogeneity, driven by a concentrated subset of highly cited studies across visual models. Additionally, high citation variance over time for specific visual models reflects distinct adoption dynamics, differentiating transitory trends from long-term influence.

6. Discussion

The visual models analyzed in this work exhibit distinct temporal trajectories. Some show a clear increasing trend, such as the RM, while others, remain relatively stable, such as the DoG, HT/SHT, and SP frameworks. Conversely, certain models display a publication trend resembling a bell-shaped curve, namely SNNs and the DT-CWT. Additionally, the analyzed visual models can be categorized into three distinct trajectories. First, GFs and DT-CWT operate as the pillars of the field, showing a robust yet dynamic profile with high production and sustained community interest. Second, the Retinex Model and SNNs represent a strong recent presence, but with high annual volatility. Finally, DoG, HT/SHT, and SP show intermittent and unpredictable behavior.

In the context of real-world applications, the GFs framework is the most prevalent based on publication volume, followed closely by the RM and SNNs frameworks. Meanwhile, the DT-CWT exhibits moderate utilization, whereas the HT/SHT and SP models remain the least frequently deployed.

Analyzing the main tasks addressed by each framework reveals that the RM is principally utilized for pattern recognition and image enhancement, whereas literature employing the DoG model primarily addresses pattern recognition, followed by classification and segmentation, respectively. In contrast, GFs are widely applied to classification, pattern recognition, and segmentation, whereas HT/SHT framework is preferred primarily for watermarking, encryption, motion analysis, and robotics. For SP, the main application domains are largely concentrated in motion analysis and robotics. Meanwhile, SNNs applications are broadly distributed across classification, segmentation, motion analysis and robotics. Finally, DT-CWT is predominantly used for watermarking and encryption applications.

In terms of task-specific selection, the GFs and SNNs models are primarily preferred for segmentation. For watermarking and encryption tasks, DT-CWT and HT/SHT represent the dominant approaches, whereas SP, RM, and SNNs represent the most widely applied architectures in motion analysis and robotics. For classification tasks, GFs represent the dominant visual model, followed by SNNs. In pattern recognition, RM and GFs are the most widely and equally utilized visual models. Finally, for image enhancement, the primary visual model corresponds to RM.

An analysis of the primary real-world applications for each model reveals that RM is used to normalize visual information to enable robust feature extraction for critical safety tasks (surface crack detection) and enhancing images for medical diagnosis (low-light cervical precancerous lesions detection). Additionally, RM is employed to restore visual fidelity in scenes with low-light allowing to work in complex workflows (mining, drilling depth tracking, power transmission line ice monitoring) and to analyze emotional features in artistic images. Besides, the RM is used as a pre-processing framework that ensures the operational reliability of autonomous systems navigating (spatial localization and mapping, tracking) and automated hazard detection in high-risk environments (coal mine exploration), both with adverse visual degradation. RM is also applied for medical diagnosis (glaucoma, deep brain tissue classification).

DoG applications handles face and human action recognition, diabetic retinopathy diagnosis, traffic sign recognition, and focusing on structural damage detection. Finally, it is utilized for segmentation of complex scenes and thermal facial image analysis.

Regarding, GFs model, it is widely used for structural healthcare monitoring, e.g., fault diagnosis in mechanical systems, medical diagnosis (including brain tumors, hyperplasia, diabetic retinopathy, and Parkinson's disease), and facial expression recognition. Also, they are applied to identify biological entities (such as fish, plants, and animal muzzles) and detect defects in materials (e.g., nozzles, leather, and steel), as well as for age estimation, sign language translation, and music chord identification. Additionally, GFs are utilized to segment and analyze railroads, lumbar discs, material cracks, nano-crystals, and retinal blood vessels. Besides, GFs are used for vision-based vibration and structural analysis.

The HT/SHT model finds application across three primary domains: medical and color image watermarking/encryption, motion analysis and robotics (3D optical flow and video-based respiration), and classification tasks, including diabetic retinopathy grading alongside non-contact vital signs monitoring. Furthermore, for segmentation and pattern recognition tasks, the HT/SHT model is used for motion-based left ventricular isolation and image correlation under illumination variations, respectively.

The SP model handles mechanics monitoring, e.g., vision-based mechanical measurements (vibrations, displacements, rotary faults) and pulsatile brain motion tracking. Additionally, it includes applications such as handwritten characters, biomedical anomalies (celiac disease, villous atrophy), and rotating machinery fault states. Also, this model covers iris recognition, face identification, and texture feature extraction applications. Besides, SP model is applied for handwritten character extraction, face authentication, and 3D contrast amplification.

SNNs exhibit the widest distribution across the investigated applications. This model finds application across multi-scale medical and agricultural segmentation; edge-directed watermarking alongside privacy-preserving homomorphic for watermarking and encryption; motion analysis and robotics (automotive optical flow, hardware-accelerated tracking, and human action aggregation); classification tasks ranging from satellite remote sensing to event-driven gesture and healthcare monitoring; pattern recognition including content-based image retrieval, and image enhancement frameworks spanning artifact suppression and event-based deblurring.

The DT-CWT is primarily used for copyright protection, secure medical image transmission, social media authentication, and video tampering detection. Additionally, it is applied for radar target identification, facial verification, kinship recognition, and the assessment of viral disease severity. Finally, the model is also utilized for driver drowsiness detection and brain tumor segmentation.

This review highlights several key insights; for example, the Retinex Model is the most widely used approach for low-light enhancement (Figures 8–10), facing virtually no competition from other models, which focus on different real-world tasks. However, in terms of pattern recognition tasks, both Retinex Model and Gabor Filters are mainly used to address the problems in this topic. Due to their mathematical definitions, only the Retinex Model and SNNs are not suitable for texture analysis, whereas the other models are widely applied for this purpose (Table 2). For classification applications (Figures 9 and 10) Gabor Filters cover the half of the works included in this review.

On the other hand, motion analysis and robotics applications are covered by almost all visual models in equal proportion (Figure 10), but the DoG model and DT-CWT have not been reported for real-world applications. A similar trend is observed in real-world watermarking and encryption applications, which are dominated by DT-CWT, followed closely by the Hermite Transform, with minimal participation from SNNs.

As shown in Table 3, all visual models incorporate a smoothing component to mitigate noise; however, Gabor Filters, the Hermite Transform, the Steerable Pyramid, and the DT-CWT are the most suitable for noise handling. In contrast, the DoG and SNNs present a moderate noise robustness level, whereas the Retinex model is the most affected by noise.

In terms of efficiency (Tables 2 and 4), Gabor Filters, the Steerable Pyramid, and Spiking Neural Networks are the most complex models regarding implementation steps, parameter counts, and computational complexity. However, this complexity is necessary for detailed image decomposition. On the other hand, the Retinex model, DoG, and DT-CWT are the least mathematically and computationally intricate models, requiring only a few parameters. In the case of the Hermite transform, it offers competitive computational complexity, low mathematical elaboration, and only two parameters, enabling complete image decomposition and analysis.

Among real-world application domains, the medical field represents a primary benchmark, accounting for 33 of the 153 works (21.5%), directed toward diagnostic support and e-health applications. Based on the analysis of these works in the medical domain, the Hermite Transform demonstrates the highest domain concentration of dedicated publications applied to medical imaging (Table 19), followed by Gabor Filters, Steerable Pyramids, and Spiking Neural Networks. In contrast, the Difference of Gaussians, the Retinex Model, and the DT-CWT exhibited lower proportions of medical deployment.

Finally, the limitations of this systematic review are detailed below. First, due to the wide heterogeneity in implementation frameworks, evaluation datasets, and performance metrics across the primary literature, a quantitative meta-analysis was not feasible. Second, standardized empirical benchmarking of operational trade-offs and hardware metrics outside the primary scope of this work.

7. Conclusions

This work presented a comprehensive systematic review following the PRISMA guidelines to evaluate the potential real-world application, temporal relevance, and task-specific utility of well-known visual models (GFs, HT/SHT, DoG, DT-CWT, RM, SNNs and SP) from 2020 to 2026 retrieved from the Scopus Dataset. An initial literature search of 595 publications in Scopus was conducted from which 153 studies were selected on pre-defined eligibility criteria. A statistics study regarding the type of publication is realized for each visual model including the image processing application. Then the five research questions are answered.

The novelty of this work derives from the systematic analysis, guided by a set of five research questions, of recent and relevant scientific articles applying bio-inspired mathematical visual models to solve image processing methods and analysis tasks. Additionally, to the best of our knowledge, this is the first systematic review to explore these visual models in a unified manner within a real-world context, rather than from a purely mathematical perspective.

The significance of this study lies in its capacity to deliver a comprehensive review of real-world applications of bio-inspired mathematical visual models by addressing five interconnected scopes: (i) it validates the temporal relevance of these visual models in resolving specific image processing tasks, (ii) it establishes a quantitative baseline regarding the overall utilization frequency of these visual models across recent literature, (iii) it maps each visual model by identifying the specific tasks they address, (iv) it identifies the preferred visual models for distinct image processing requirements, and (v) it details the specific real-world applications in which each visual model is applied.

By addressing the established research questions across the selected studies, several key paradigms regarding the deployment of visual models in recent real-world applications have highlighted.

Thus, despite being developed decades ago, these visual models remain highly relevant, retaining their validity even amidst the integration of deep learning and generative paradigms. The temporal trend analysis highlights four predominant models: RM, SNNs, GFs, and DT-CWT. Furthermore, regarding their utility in practical applications, RM, SNNs, and GFs emerge as the most dominant approaches.

On the other hand, visual model selection is strictly driven by task-specific computational demands rather than universal applicability. Security applications (watermarking and encryption) prefer transform-domain analysis (DT-CWT, HT/SHT), whereas dynamic environments (motion analysis and robotics) rely on spatiotemporal processing (SP, SNNs). Meanwhile, segmentation and classification tasks leverage frequency and neural dynamics (GFs, SNNs), with RM and GFs maintaining niche dominance in illumination enhancement and feature extraction.

Regarding real-world applications, RM serves as a relevant preprocessing framework for autonomous navigation systems, hazard detection, and medical diagnosis support. DoG stands out in facial, human action, and specific pattern recognition, as well as structural damage detection. GFs are also applied to structural health monitoring, biological entity identification, facial expression recognition, medical diagnosis, and material defect detection. On the other hand, HT/SHT have shown their applicability in medical and color image watermarking and encryption, as well as motion analysis and robotics. SP is applied to mechanical monitoring, handwritten character recognition, and biomedical anomaly detection. In contrast, SNNs exhibit the widest distribution of applications, ranging from medical and agricultural segmentation to watermarking, optical flow, remote sensing classification, image retrieval, and image enhancement. Finally, DT-CWT is mainly used for copyright protection and other specific tasks such as facial and kinship recognition, driver drowsiness detection, and brain tumor detection.

Furthermore, this study highlights that the recent peak of SNNs applications, along with the well-known stability of classical models like DT-CWT, HT/SHT, DoG, and SP, opens promising opportunities for hybrid deep learning frameworks. By leveraging the image enhancement performance of RM and the versatility of GFs, these hybrid architectures can integrate directional filtering strengths (DT-CWT), multi-scale capabilities (DoG, SP), perfect image reconstruction (HT/SHT) and robust feature extraction (SNNs) with the advanced learning capabilities of next-generation machine learning paradigms.

Future work will focus on analyzing and characterizing the performance of each visual model across their respective image processing tasks. This will be achieved by establishing a comprehensive framework that outlines their distinct strengths and limitations, rather than merely comparing quantitative metrics across different visual models. Additionally, a future review will explore hybrid deep learning approaches that incorporate these bio-inspired mathematical visual models.

Author Contributions: Conceptualization, E.M.-A. and J.B.; methodology, E.M.-A. and J.B.; software, E.M.-A. and J.B.; validation, E.M.-A. and J.B.; formal analysis, E.M.-A. and J.B.; investigation, J.B. and E.M.-A.; resources, E.M.-A. and J.B.; data curation, E.M.-A. and J.B.; writing—original draft preparation, E.M.-A. and J.B.; writing—review and editing, E.M.-A. and J.B.; visualization, E.M.-A. and J.B.; supervision, E.M.-A. and J.B.; project administration, E.M.-A. and J.B.; funding acquisition, E.M.-A. and J.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All bio-inspired mathematical models of the human visual system and their real-world image processing applications reviewed in this study are derived from published literature cited in the text. The literature extraction matrix, PRISMA screening records, data extraction spreadsheets, and associated MATLAB and Python processing scripts are available from the corresponding author upon reasonable request.

Acknowledgments: Ernesto Moya-Albor and Jorge Brieva would like to thank the Facultad de Ingeniería de Universidad Panamericana for all support in this work. During the preparation of this work, the authors used Gemini 3.5 to assist with drafting and editing portions of the manuscript and to improve English writing and style. The authors have reviewed and edited the content as needed and take full responsibility for the content of the published article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CBIR	Content-based Image Retrieval
DoG	Difference of Gaussians
DT-CWT	Dual-Tree Complex Wavelet Transform
DWT	Discrete Wavelet Transform
GANs	Generative Adversarial Networks
GFs	Gabor Filters
HT	Hermite Transform
HVS	Human Visual System
IQA	Image Quality Assessment
LoG	Laplacian of Gaussian
MHT	Multiscale Hermite Transform
MSR	Multi-Scale Retinex
OSF	Open Science Framework
RF	Receptive Fields
RM	Retinex Model
SHT	Steered Hermite Transform
SIFT	Scale-Invariant Feature Transform
SLR	Systematic Literature Review
SMHT	Steered Multiscale Hermite Transform
SNNs	Spiking Neural Networks
SP	Steerable Pyramid
SRM	Spike Response Model
SSR	Single-Scale Retinex
ViTs	Vision Transformers

Appendix A

Table A1. Supplementary list of journals with a single publication. Open Access Category (OAC): Gold (Gd), Hybrid (H), Green (Gr), Bronze (B).

Journal Name	Articles	OAC
Acta Cytologica	1	
Advances in Electronics, Computer, Physical and Chemical Sciences	1	CH *
Advances in Engineering and Intelligence Systems	1	
Arabian Journal for Science and Engineering	1	
Automation in Construction	1	
Big Data Mining and Analytics	1	GdGr
Biomedical Signal Processing and Control	1	

Table A1. Cont.

Journal Name	Articles	OAC
Biomimetics	1	GdGr
Circuits, Systems, and Signal Processing	1	
Cluster Computing	1	GdHGr
Communications in Computational Physics	1	
Computer Systems Science and Engineering	1	Gd
Computers and Electrical Engineering	1	
Computers and Electronics in Agriculture	1	
Computers in Industry	1	
Complex and Intelligent Systems	1	GdGr
Concurrency and Computation: Practice and Experience	1	
Current Biology	1	GdHGr
Cybernetics and Systems	1	
Diagnostics	1	GdGr
Drones	1	GdGr
Engineering Research Express	1	
Engineering Proceedings	1	GdGr
Engineering, Technology and Applied Science Research	1	Gd
Evolutionary Intelligence	1	
Fire	1	GdGr
Heliyon	1	GdGr
IEEE Signal Processing Letters	1	
IEEE Transactions on Cognitive and Developmental Systems	1	
IEEE Transactions on Geoscience and Remote Sensing	1	
IEEE Transactions on Image Processing	1	
IEEE Transactions on Instrumentation and Measurement	1	
IEEE Transactions on Very Large Scale Integration (VLSI) Systems	1	
IEICE Transactions on Electronics	1	B
Image and Vision Computing	1	
Indonesian Journal of Electrical Engineering and Computer Science	1	GdGr
Information (Switzerland)	1	GdGr
Information Processing and Management	1	
Informatica (Slovenia)	1	Gd
Ingenierie des Systemes d'Information	1	GdH
International Arab Journal of Information Technology	1	Gd
International Journal of Advanced Computer Science and Applications	1	Gd
International Journal of Computer Applications in Technology	1	GdH
International Journal of Computer Theory and Engineering	1	Gd
International Journal of Computer Vision	1	GdH
International Journal of Computational Intelligence Systems	1	GdGr
International Journal of Computational Vision and Robotics	1	
International Journal of Computing Science and Mathematics	1	
International Journal of Engineering Trends and Technology	1	
International Journal of Imaging Systems and Technology	1	
International Journal of Intelligent Systems and Applications in Engineering	1	
International Journal of Manufacturing Technology and Management	1	
International Journal of Reasoning-based Intelligent Systems	1	
International Journal of Reconfigurable and Embedded Systems	1	GdGr
International Journal of Sensor Networks	1	
International Journal of System Assurance Engineering and Management	1	
International Journal of Information and Communication Technology	1	
International Journal on Advanced Science, Engineering and Information Technology	1	GdH
International Journal on Communications Antenna and Propagation	1	
Journal of Ambient Intelligence and Humanized Computing	1	
Journal of Artificial Intelligence and Soft Computing Research	1	Gd
Journal of Civil Structural Health Monitoring	1	

Table A1. Cont.

Journal Name	Articles	OAC
Journal of Digital Imaging	1	Gr
Journal of Donghua University (English Edition)	1	
Journal of Imaging	1	GdGr
Journal of Information Processing Systems	1	
Journal of Nondestructive Evaluation	1	
Journal of Vibration Engineering and Technologies	1	
Journal of Visual Communication and Image Representation	1	
Journal on Advances in Signal Processing	1	GdGr
Life	1	GdGr
Magnetic Resonance in Medicine	1	GdHGr
Marine Geology and Quaternary Geology	1	
Mechanical Systems and Signal Processing	1	
Multimedia Systems	1	
Nanomaterials	1	GdGr
Network: Computation in Neural Systems	1	
Neurocomputing	1	
Optical Engineering	1	
Optical Memory and Neural Networks (Information Optics)	1	
Optics and Laser Technology	1	
Optik	1	
Pattern Recognition	1	GdH
Periodica Polytechnica Civil Engineering	1	Gd
Photonics	1	GdGr
Process Safety and Environmental Protection	1	
Processes	1	Gd
Sensing and Imaging	1	
Sensors	1	GdGr
Sensors (Switzerland)	1	GdGr
Signal Processing	1	
Technologies	1	GdGr
TEM Journal	1	Gd
Turkish Journal of Electrical Engineering and Computer Sciences	1	Gd
Visual Computer	1	
Wuhan University Journal of Natural Sciences	1	

* Book chapter.

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