Advancements in Texture Analysis and Classification: A Bibliometric Review of Entropy-Based Approaches

Muqaddas Abid[1], Muhammad Suzuri Hitam[2]*, Rozniza Ali[3], Muhammad Hammad[4]
Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, Malaysia[1, 2, 3]
Faculty of Business, Economics and Social Development, Universiti Malaysia Terengganu, Malaysia[4]

***Abstract*—Entropy-based texture analysis has gained significant attention in medical imaging, computer vision, and material science. The purpose of this paper is to provide a bibliometric review that maps the evolution, key contributors, research trends, and emerging themes of entropy-based texture analysis from 1980 to 2025. Using the Scopus database, 1,482 articles were initially retrieved and refined to 1,226 documents for analysis. VOSviewer was employed for bibliometric mapping, examining publication trends, authorship networks, keyword co-occurrence, and citation patterns. Results indicate a notable increase in research activity between 2004 and 2021, followed by a decline in recent years. The analysis highlights leading contributors, with significant work focusing on medical imaging applications such as radiomics and tumor heterogeneity assessment. While Shannon entropy remains widely used, newer measures like sample entropy, permutation entropy, and dispersion entropy are gaining attention. The study also identifies major research clusters, demonstrating the interdisciplinary nature of entropy-based texture analysis across medicine, engineering, and artificial intelligence. Despite database and language limitations, this review provides valuable insights into the field's evolution and future directions, encouraging further interdisciplinary collaborations and advancements.**

Keywords*—Artificial intelligence; bibliometric review; entropy; research trends; texture analysis

I. Introduction

Texture is a fundamental characteristic of images and plays a significant role in various image processing tasks [1]. Although no universally accepted definition of texture exists, it is commonly understood as a representation of pixel intensity or color variations that form recurring patterns [2]. Early computational studies on texture began with Julesz's work, leading to extensive research in texture classification, segmentation, synthesis, and shape reconstruction [3]. Among these, classification involves assigning an image or a region to a predefined texture category, while segmentation focuses on partitioning an image into regions with homogeneous textures. Texture synthesis, on the other hand, aims to generate new images that closely resemble a given texture sample. Additionally, texture analysis has been explored for three-dimensional shape reconstruction from images, although this aspect has received comparatively less attention [4].

The foundation of texture analysis lies in computing meaningful features that effectively describe texture patterns. Various mathematical models have been proposed to quantify texture, and over the years, numerous theories and algorithms have been developed to facilitate texture analysis. One of the earliest approaches was inspired by human visual perception, leading to the introduction of co-occurrence matrices. Human perception of texture has significantly influenced computer-based analysis, particularly through the development of texton theory, which suggests that texture discrimination relies on specific fundamental elements called textons. Initially, these textons were described as basic components such as blobs, corners, and edges, but later, they were redefined as cluster centers in a filter response space. This reformulation provided a computational framework for automatic texton generation, enabling advancements in learning-based texture analysis [5].

Among the various methods developed for texture and signal characterization, entropy-based approaches have received widespread attention due to their ability to quantify the degree of randomness, uncertainty, and complexity inherent in data. Originating from Shannon's foundational work in information theory [6], entropy has evolved into a core concept used extensively in analyzing one-dimensional (1D) time-series data.

Over the years, a wide range of 1D entropy measures have been introduced and further refined, such as Approximate Entropy (ApEn) [7], Sample Entropy (SampEn) [8], Permutation Entropy (PermEn) [9], Dispersion Entropy (DispEn) [10], Distribution Entropy (DistrEn) [11], and Increment Entropy (IncrEn) [12]. These measures have demonstrated considerable utility across a variety of domains including biomedical signal analysis, financial time-series forecasting, fault diagnosis in mechanical systems, and acoustic signal processing, where they are employed to capture non-linear dynamics, irregularities, and the underlying complexity of 1D signals [13, 14, 15, 16].

Despite the success of entropy in 1D analysis, applying similar principles to two-dimensional (2D) image textures presents unique challenges. Images contain spatial dependencies and structural variations that differ fundamentally from time-series data. To bridge this gap, several bi-dimensional entropy measures have been developed that extend the core ideas of entropy to better capture the spatial complexity and texture patterns present in images. Notable examples include 2D Sample Entropy [17], 2D Approximate Entropy [18], 2D Dispersion Entropy [19], 2D Distribution Entropy [20], 2D Permutation Entropy [9], 2D Fuzzy Entropy [21], and 2D

*Corresponding authors

Increment Entropy [22]. These methods provide enhanced capabilities for texture analysis, making them particularly valuable for applications in medical image processing, industrial inspection, and remote sensing [23].

Few studies have attempted to review or quantitatively analyze entropy-related research. For example, Li et al. [24] provided a bibliometric overview of entropy research in general, while Lam et al. [25] conducted a bibliometric analysis of information-theoretic studies. Similarly, surveys on texture analysis [1, 4, 5] have discussed a variety of statistical and transform-based approaches. However, none of these works specifically examine the role of entropy-based methods in texture analysis and classification. Examining this aspect is crucial for guiding future research and encouraging interdisciplinary collaboration. This study addresses this gap by providing a bibliometric review of entropy-based texture analysis and classification methods from 1980 to 2025. The novelty of this review lies in its focused scope: unlike earlier bibliometric studies that addressed entropy in general or information-theoretic approaches, this work systematically analyzes entropy-based texture analysis and classification across four decades (1980–2025). By identifying research clusters, leading contributors, and underexplored areas such as the limited adoption of advanced bidimensional entropy measures in medical imaging, the study provides original insights and highlights opportunities for future research.

By analyzing research publications, citation patterns, and emerging trends, this paper seeks to provide valuable insights into the development and application of entropy measures in texture analysis. The primary objectives of this study are threefold: 1) to analyze publication trends in entropy-based texture analysis, 2) to identify leading contributors and top-cited papers, and 3) to uncover emerging research themes and collaborative networks within the field.

The remainder of this paper is structured as follows: Section II presents the methodology employed for bibliometric analysis, including data collection and analysis techniques. Section III discusses the results of analysis, highlighting the most influential studies, research collaborations, and emerging trends. Finally, Section IV concludes the paper by summarizing key findings and the future directions in entropy-based texture analysis.

II. Materials and Methods

A. Search Strategy

To conduct a comprehensive bibliometric analysis on texture analysis and classification, a systematic search strategy was employed. The Scopus database was selected as the primary source due to its extensive coverage of high-impact research publications in the domains of computer science, medical imaging, and artificial intelligence.

A search string was formulated to include a broad spectrum of entropy-based methodologies relevant to texture analysis using the Scopus database. The keywords incorporated terms such as “texture analys” and “texture classification”, combined with various entropy measures, including “shannon entropy”, “bidimension* entropy”, “multiscale entropy”, “spatial qentropy”, “Renyi entropy”, “dispersion entropy”, “distribution entropy”, “increment entropy”, “permutation entropy”, “refined composite multiscale entropy”, “fuzzy entropy”, and “espinosa entropy”. The Boolean operator” OR” was used to maximize inclusion, and the search was restricted to titles, abstracts, and keywords (TITLE-ABS-KEY) to ensure precision. The final search query used in the Scopus database is shown in Table I.

TABLE I. Search String

Source	Search string
Scopus	TITLE-ABS-KEY (“texture analysis” OR “texture classification”) AND TITLE-ABS-KEY (“entropy” OR “bidimension* entropy” OR “Shannon entropy” OR “multiscale entropy” OR “spatial entropy” OR “Renyi entropy” OR “dispersion entropy” OR “distribution entropy” OR “increment entropy” OR “permutation entropy” OR “refined composite multiscale” OR “fuzzy entropy” OR “espinosa entropy”)

B. Data Collection and Filtering

Using the specified search string, a total of 1,482 research articles were initially retrieved. To refine the dataset, the inclusion and exclusion criteria (outlined in Table II) were applied. After applying the inclusion-exclusion criteria, a total of 1226 documents were retrieved for further analysis. In this bibliometric review, the dataset consists of 1,226 research documents on entropy-based texture analysis retrieved from the Scopus database (1980–2025). This data set forms the basis for all subsequent bibliometric analyses.

TABLE II. Selection Criteria for Bibliometric Analysis

Criterion	Inclusion	Exclusion
Timeline	1980–2025	Before 1980
Language	English	Non-English
Document Type	Journal articles and conference proceedings	Books, book chapters, and review papers

C. Bibliometric Analysis and Visualization

The bibliometric analysis was conducted using VOSviewer version 1.6.19, a widely recognized tool developed by van Eck and Waltman at Leiden University [26]. VOSviewer enables advanced bibliometric mapping through co-authorship, co-citation, and keyword cooccurrence analysis. The software specializes in network visualization, allowing the identification of emerging research trends and collaborations in the field of texture analysis. The dataset exported from Scopus was processed in Plaintext format and contained bibliometric information such as publication year, article title, author names, journal name, number of citations, and keywords.

D. Analysis Procedures

To gain a deeper understanding of the research landscape, the following analyses were conducted:

- Publication trend analysis: Evaluating the growth of entropy-based research in texture analysis over time.
- Authorship and collaboration analysis: Identifying influential researchers and co-authorship networks.

- Keyword co-occurrence analysis: Mapping frequently used terms to detect emerging research themes.
- Citation and co-citation analysis: Identifying highly cited papers, leading authors, and influential journals.

VOSviewer's clustering algorithms were used to visualize the relationships among keywords and authors, offering insights into research trends. The density visualization features further highlighted the dominant research areas in the field. While this study provides valuable insights into the evolution of texture analysis and entropy-based methodologies, certain limitations must be acknowledged:

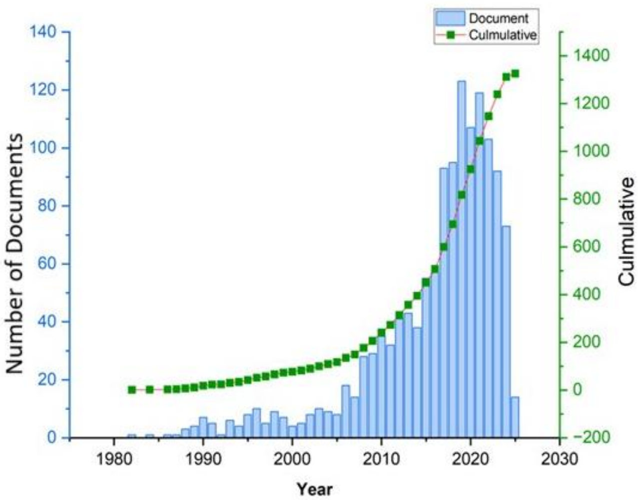

Fig. 1. Publications trend from year 1980 to 2025.

- Database bias: The analysis is restricted to the Scopus database, which may exclude relevant studies indexed in other databases such as Web of Science, IEEE Xplore, or PubMed.
- Language restriction: Non-English publications were excluded, potentially omitting significant contributions from non-English-speaking researchers.
- Document type restriction: Excluding books and review articles may limit the study's scope regarding theoretical advancements in the field.

Despite these limitations, the study ensures comprehensive and replicable bibliometric analysis, providing valuable insights into the evolution of entropy-based texture analysis methodologies.

III. Results and Discussion

A. Publication Trends

Fig. 1 presents the trend of document publications over the years 1980 to 2025. The analysis reveals an overall increasing trend in the number of documents published, with notable fluctuations at certain points.

In the years 2004-2014, the number of published documents showed a gradual rise, with occasional minor fluctuations. Around 2016, a significant increase in publications indicated an increase in research activity during that period. This upward trend continued, reaching its peak between 2018 and 2021 when the number of publications exceeded 100 per year.

Post-2021, the number of documents began to decline, showing a steady drop from 2022 onward. The decline is more pronounced in 2024 and 2025, with a sharp decrease in published documents. However, the low number of publications in 2025 can likely be attributed to the fact that the year has only recently begun, meaning that more documents may still be in the publication process and will be added later in the year.

Overall, the trend shows strong research momentum during the late 2010s and early 2020s, followed by a recent decline in publications.

B. Publications by Authors

The leading contributors in entropy-based texture analysis are presented in Table III emphasizing their publication volume. A stark contrast is evident, with Ganeshan, B. significantly outpacing other researchers in terms of the number of published documents. This initially suggests a dominant influence in the field; however, upon closer examination of the search results, it becomes apparent that while Ganeshan's work has had a profound impact on texture analysis, it does not predominantly focus on entropy-based methods. Instead, his contributions are more aligned with radiomics and broader quantitative imaging techniques.

In contrast, the other authors listed, Laghi, A., Schieda, N., Horger, M., Humeau Heurtier, A., and others, have more explicitly engaged in research utilizing entropy-based methodologies. Their work focuses on applying various entropy measures to medical imaging and pattern recognition, suggesting a more targeted exploration of entropy-driven texture characterization. This distinction is crucial, as it highlights that while Ganeshan's influence on texture analysis is significant, advances in entropy-based techniques are more directly attributable to the collective efforts of the remaining authors.

TABLE III. Most Contributing Authors

Rank	Author	Institution	Country	TP	TC	TP/TC	h-index
1	Ganeshan, Balaji	University College London	United Kingdom	48	3142	0.015	26
2	Laghi, Andrea	Faculty of Medicine and Psychology	Italy	11	417	0.026	10
3	Schieda, Nicola	L'Hôpital d'Ottawa	Canada	11	564	0.020	10
4	Costa, André Luiz Ferreira	Postgraduate Program in Dentistry	Brazil	10	82	0.122	6
5	Horger, Marius Stefan	Universitätsklinikum und Medizinische Fakultät Tübingen	Germany	10	134	0.075	8
6	Humeau-	Université d'Angers	France	10	214	0.047	8

	Heutier, Anne						
7	Liu, Song	Medical School of Nanjing University	China	10	345	0.029	9
8	Pattichis, C. S.	University of Cyprus	Cyprus	10	210	0.048	6
9	Zhou, Zhengyang	Nanjing University of Chinese Medicine	China	10	341	0.029	9
10	He, Jian	Medical School of Nanjing University	China	9	329	0.027	9

TP = Total Publications; TC = Total Citations

The presence of researchers such as Pattichis, C.S., Zhou, Z., and Costa, A.L.F., who have made substantial contributions to signal processing and biomedical image analysis, further reinforces the relevance of entropy-based approaches in these domains. Their work likely incorporates entropy measures for feature extraction, classification, and diagnosis, making direct contributions to methodological advancements.

This observation underscores the importance of contextualizing publication volume with a research focus. While high publication counts can indicate strong influence, a more nuanced assessment reveals that true progress in entropy-based texture analysis is driven by a broader set of contributors. In the future, fostering collaborations among researchers specializing in entropy-based methods and those with expertise in broader radiomics approaches could lead to more comprehensive advancements in texture characterization.

C. Leading Subject Areas

The distribution of documents by subject area provides valuable insights into the interdisciplinary impact of entropy-based texture analysis. Fig. 2 highlights that the majority of research contributions fall under Medicine (32.9%), followed by Computer Science (16.6%), Engineering (14.7%), and Biochemistry, Genetics, and Molecular Biology (8.3%).

Entropy-based texture analysis is extensively used in medical imaging and diagnostics, particularly in radiology, histopathology, and MRI/CT scan analysis [27]. The ability of entropy measures to quantify texture variations in biomedical images makes them instrumental in disease detection, including cancer classification, neurological disorders, and cardiovascular abnormalities. The high percentage of publications in medicine underscores the growing adoption of entropy-driven methodologies in clinical research and healthcare applications.

The significant presence of entropy-based texture analysis in computer science reflects its role in image processing, artificial intelligence, and machine learning applications. Researchers employ entropy as a key feature extraction technique in deep learning and pattern recognition models, contributing to advancements in automated medical diagnosis [28, 29], remote sensing [30, 31], and security-based image analysis [32].

Engineering applications of entropy-based texture analysis span multiple domains, including material characterization, structural health monitoring [33], and non-destructive testing [34]. Entropy measures help analyze surface textures in industrial applications, facilitating defect detection and quality control in manufacturing processes [35].

This distribution highlights the dominant role of entropy-based texture analysis in medicine and computer science, demonstrating its significance in medical imaging, artificial intelligence, and material science applications. The interdisciplinary nature of entropy methods indicates their potential for further advancements across biomedical, engineering, and computational fields.

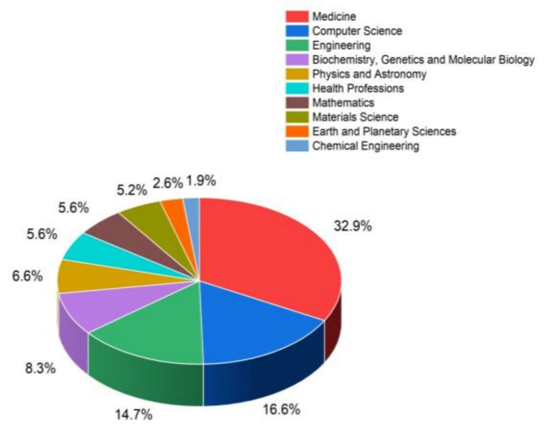

Fig. 2. Statistics of entropy-based texture analysis with respect to area of application.

D. Top Cited Papers

Table IV presents highly cited papers in entropy-based texture analysis. A bibliometric analysis of highly cited papers in texture analysis and entropy reveals that while texture analysis is widely used for medical image analysis, explicit utilization of advanced entropy-based features remains limited. Most of these studies incorporate Shannon entropy as one of the texture features, indicating that entropy is recognized as an important measure for texture characterization. This reinforces the role of entropy in assessing image complexity and heterogeneity. However, the more recently emerged bidimensional entropy measures such as Sample Entropy ($SampEn_{2D}$), Dispersion Entropy ($DispEn_{2D}$), and Permutation Entropy ($PermEn_{2D}$) are not extensively utilized in these highly cited works.

The reason for this gap is likely the timeline of their development. Many of the papers in our analysis were published before these advanced entropy measures gained attraction in medical image analysis. As a result, traditional texture descriptors, particularly those derived from the Gray-Level Co-occurrence Matrix (GLCM) [46] and statistical methods [47, 48], remain dominant. This gap highlights an opportunity for future research: leveraging bidimensional entropy measures in texture-based radiomics could provide novel insights into tumor heterogeneity and improve classification performance. Exploring these measures further may enhance predictive modeling and disease characterization beyond the capabilities of conventional texture features.

TABLE IV. TOP 10 HIGHLY CITED PAPERS IN ENTROPY-BASED TEXTURE ANALYSIS

Title	Authors	Year	Source Title	Citations
Assessment of primary colorectal cancer heterogeneity by using whole-tumor texture analysis [36]	Ng, F., Ganeshan, B., Kozarski, R., Miles, K.A., Goh, V.	2013	Radiology	380
Haralick texture analysis of prostate MRI: utility for differentiating non-cancerous prostate from prostate cancer [37]	Wibmer, A., Hricak, H., Gondo, T., Sala, E., Vargas, H.A.	2015	European Radiology	346
Assessment of response to tyrosine kinase inhibitors in metastatic renal cell cancer [38]	Goh, V., Ganeshan, B., Nathan, P., Vinayan, A., Miles, K.A.	2011	Radiology	327
Assessment of tumor heterogeneity by CT texture analysis: Can the largest crosssectional area be used as an alternative to whole tumor analysis? [39]	Ng, F., Kozarski, R., Ganeshan, B., Goh, V.	2013	European Journal of Radiology	316
Reproducibility of tumor uptake heterogeneity characterization throug h textural feature analysis in 18F-FDG PET [40]	Tixier, F., Hatt, M., Le Rest, C.C., Corcos, L., Visvikis, D.	2012	Journal of Nuclear Medicine	289
Tumour heterogeneity in oesophageal cancer assessed by CT texture analysis [41]	Ganeshan, B., Skogen, K., Pressney, I., Coutroubis, D., Miles, K.	2012	Clinical Radiology	278
Texture analysis of non-small cell lung cancer on unenhanced CT [42]	Ganeshan, B., Abaleke, S., Young, R.C.D., Ch atwin, C.R., Miles, K.A.	2010	Cancer Imaging	277
Practical guidel ines for choosing GLCM textures for landscape classification [43]	Hall-Beyer, M.	2017	International Journal of Remote Sensing	276
Can quantitative CT texture analysis differentiate fat-poor renal angiomyolipoma from renal cell carcinoma? [44]	Hodgdon, T., McInnes, M. D.F., Schieda, N., La mb, L., Thornhill, R.E.	2015	Radiology	246
CT textural analysis of hepatic metastatic colorectal cancer [45]	Lubner, M.G., Stabo, N., Lubner, S.J., Halberg, R.B., Pickhardt, P.J.	2015	Abdominal Imaging	237

E. Keyword Analysis

Fig. 3 shows a network map of keyword co-occurrence of a published article on texture analysis. The keyword co-occurrence network map provides an overview of the thematic structure in entropy-based texture analysis research. Larger nodes represent frequently occurring terms while connecting lines indicate co-occurrences in published studies. Different clusters, distinguished by color, reveal key research directions. The green cluster relates to imaging techniques, encompassing terms such as “magnetic resonance imaging (MRI)”, “neural networks”, and “microstructure”. The inclusion of “high entropy alloy” suggests that entropy-based texture analysis extends beyond medical imaging, playing a role in materials science for characterising microstructural patterns. At the center of the network, “texture analysis” emerges as the most dominant keyword, closely linked with “image processing”, “feature extraction”, and “classification”, reflecting the methodological focus on extracting meaningful features for applications in medical imaging and pattern recognition. Fig. 3 illustrates the keyword co-occurrence map for entropy-based texture analysis documents, whereas Table V lists the top 10 keywords along with their total link strengths.

TABLE V. TOP 10 KEYWORDS IN ENTROPY-BASED TEXTURE ANALYSIS

Keyword	Occurrence	Link Strength
Texture Analysis	501	673
Magnetic Resonance Imaging	120	208
Radiomics	70	135
Computed Tomography	67	114
Texture	62	96
Entropy	58	87
Image Processing	38	71
Classification	35	66
GLCM	34	43
Texture Classification	34	28

The red cluster represents the core computational techniques, featuring keywords such as “entropy”, “GLCM” (grey-level co-occurrence matrix), “feature extraction”, and “wavelet transform”. The inclusion of “fractal dimension” and “Gabor filters” highlights the mathematical approaches used to quantify texture complexity. The blue cluster focuses on medical imaging applications, with terms such as “Computed

Tomography (CT)", "MRI", "PET/CT", and disease-related keywords like "lung cancer", "glioblastoma", and "metastasis", demonstrating the increasing role of entropy-based texture analysis in radiomics and diagnostic imaging. Meanwhile, the yellow and orange clusters highlight its clinical relevance, featuring keywords such as "diagnosis", "differential diagnosis", "colorectal cancer", and "gastric cancer", which emphasize its role in quantitative imaging-based diagnostics to support clinical decision-making.

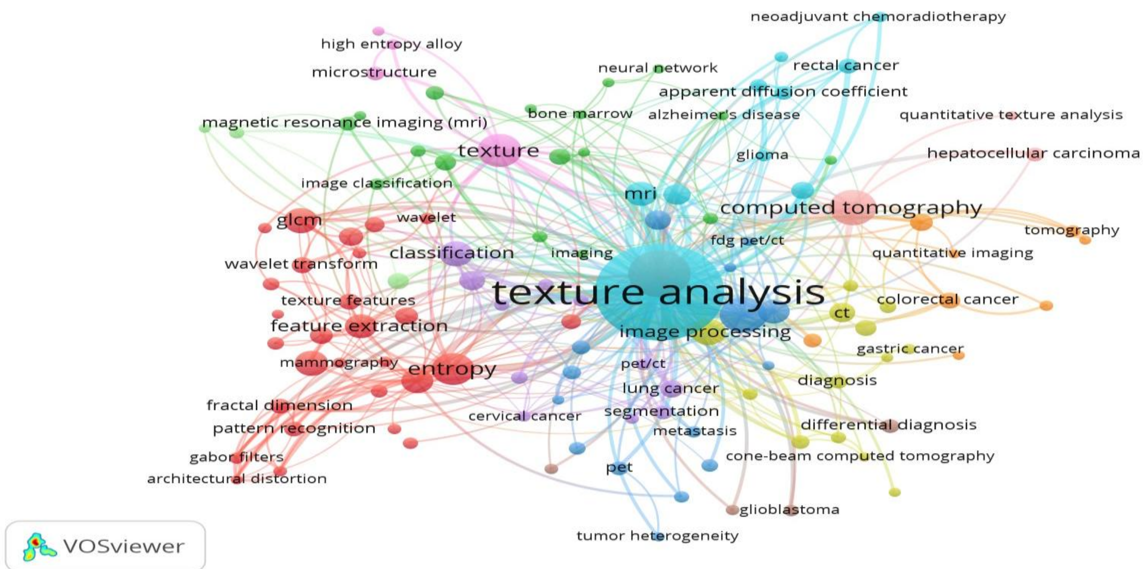

Fig. 3. Keyword co-occurrence map.

The overlay visualisation map in Fig. 4 illustrates the evolution of research trends in entropy-based texture analysis over time. Keywords shown in yellow represent emerging areas of interest, indicating the current focus of research. Recent studies highlight topics such as quantitative texture analysis, radiomics, lung cancer, MRI, computed tomography, and machine learning, suggesting a growing emphasis on advanced medical imaging techniques. In contrast, terms like entropy, feature extraction, and classification appear in green and blue, signifying their established role in the field. This progression suggests a shift from traditional texture analysis methods towards more sophisticated, imaging-driven diagnostics. Given these trends, future research is likely to further explore the integration of texture features with cutting-edge computational techniques, reinforcing their application in medical and technological advancements. The strong connections between feature extraction techniques and medical imaging terms suggest that the field is evolving towards automated and quantitative radiomics approaches. The presence of diverse methodological and application-focused clusters suggests that future research will continue refining computational techniques while expanding their use in clinical and material sciences.

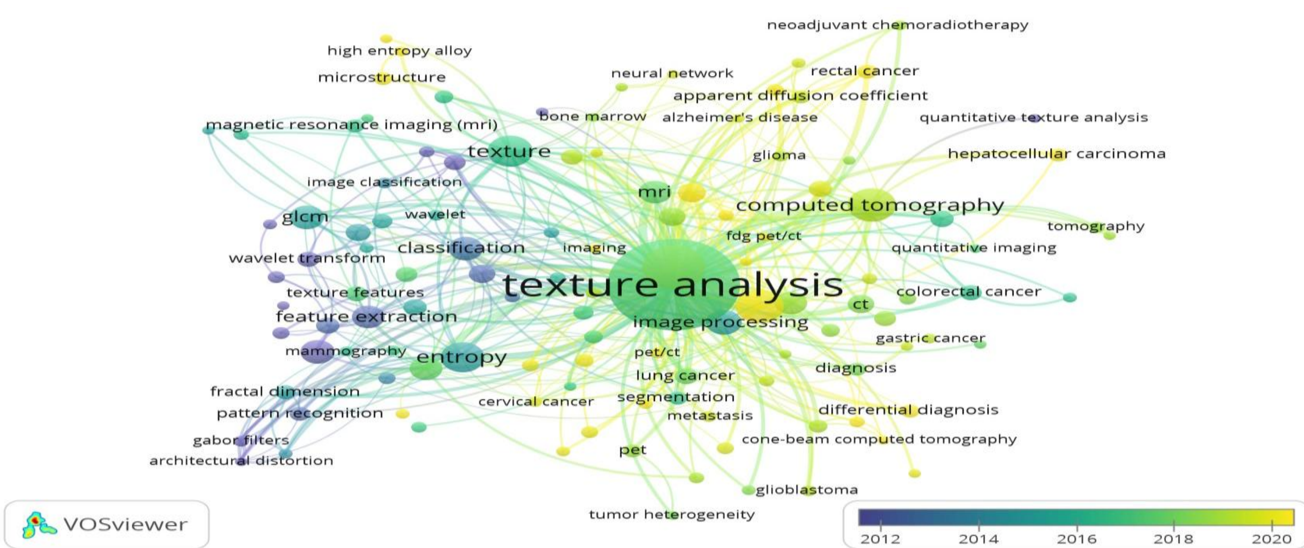

Fig. 4. Keywords overlay visualization map.

F. Geographic Contribution Analysis

The country co-authorship map presented in Fig. 5 illustrates the international collaborative landscape in the field, where each node represents a country and the lines (edges) indicate co-authorship links. The size of the node corresponds to the volume of publications, while the thickness of the links reflects the strength of collaborative ties. Countries are grouped into clusters based on the strength and frequency of their co-authorship patterns, with each cluster represented by a distinct color. Notably, China, the United Kingdom, India, and Germany appear as central hubs with extensive co-authorship ties spanning across multiple clusters, underscoring their dominant roles in facilitating global research collaboration. The green cluster, which includes countries such as India, Poland, and Saudi Arabia, represents a growing network of emerging contributors, particularly from Asia and Eastern Europe. Similarly, the red cluster, dominated by France, Brazil, Canada, and Turkey, reflects strong intercontinental research partnerships, particularly between Europe and the Americas. The blue cluster, comprising Japan, Singapore, Taiwan, and Indonesia, highlights robust regional cooperation in East and Southeast Asia. Meanwhile, the yellow cluster, centered around China and the United Kingdom, demonstrates cross-regional collaboration that bridges Asia and Europe. Countries like Italy and Mexico form part of the orange cluster, indicating active participation in Europe-Asia scientific exchanges. The inclusion of Australia and Finland in separate clusters (purple) suggests their specialised contributions and unique collaborative pathways, often acting as bridges between regions. The map's overall structure and the interconnectedness of nodes suggest a highly collaborative global research ecosystem, with developing nations increasingly integrated into international scholarly networks.

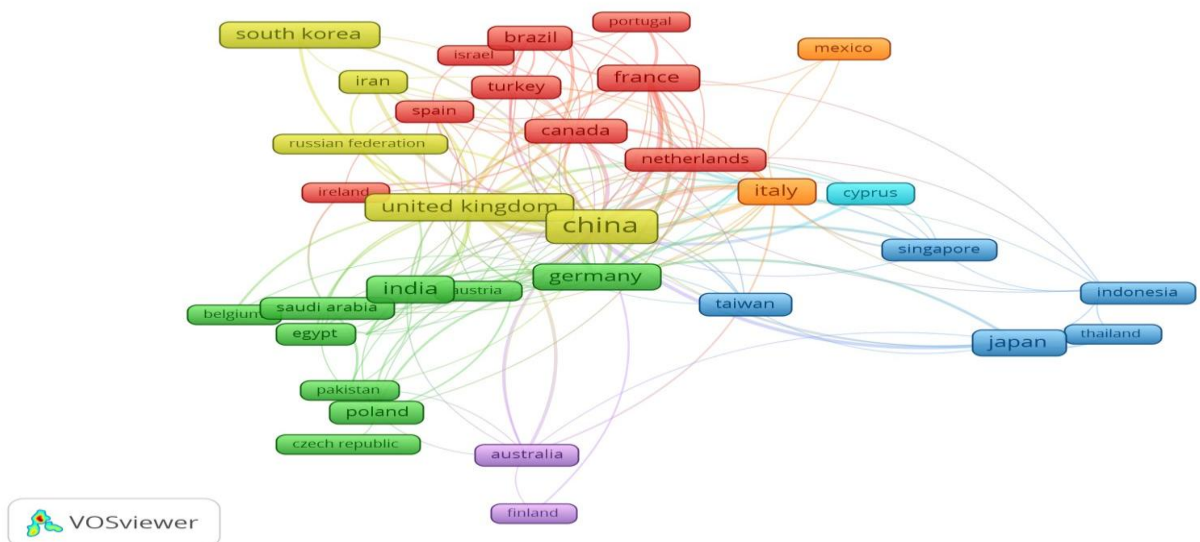

Fig. 5. Country co-authorship network.

IV. Conclusion

This bibliometric study provides a quantitative overview of entropy-based texture analysis, highlighting its growth, key contributors, and major applications. The results indicate that research in entropy-based texture analysis has experienced significant growth from 2004 to 2021, with peak activity between 2018 and 2021, followed by a decline in recent years. The findings reveal that medical imaging, particularly radiomics and tumor heterogeneity assessment, remains the dominant application area. Keyword analysis and citation mapping indicate that Shannon entropy continues to be widely used, but newer entropy measures such as sample entropy, permutation entropy, and dispersion entropy are emerging as promising techniques.

Furthermore, the study identifies strong international collaborations, with China, the United Kingdom, India, and Germany being key contributors. The interdisciplinary nature of entropy-based texture analysis is evident, spanning domains such as artificial intelligence, biomedical imaging, and material science. Despite its established applications, the field faces challenges related to standardization, computational efficiency, and interpretability of entropy measures.

A. Critical Insights and Future Directions

While this bibliometric review identifies major trends and contributors in entropy-based texture analysis, several methodological gaps remain. First, many highly cited studies still rely heavily on Shannon entropy or GLCM-based descriptors, whereas more advanced measures such as sample entropy, dispersion entropy, permutation entropy, and bidimensional variants are underutilized. This indicates a need for more comparative studies that evaluate the relative strengths and limitations of different entropy measures in diverse applications.

Second, there is a lack of standardized evaluation frameworks for entropy-based texture classification. Current studies often use different data sets, preprocessing pipelines, and classification methods, which makes direct comparisons difficult. Establishing benchmark datasets and protocols could help ensure reproducibility and enable fair performance assessment across entropy measures.

Third, emerging application areas remain relatively unexplored. Although medical imaging dominates, entropy-based texture analysis also shows promise in materials science, industrial inspection, structural health monitoring, and security applications. For example, in industrial inspection, entropy measures can characterize surface roughness and detect micro-defects in manufacturing processes, enabling non-destructive quality control. In remote sensing, entropy-based features have been employed to classify land cover types, monitor vegetation patterns, and detect environmental changes from satellite imagery. Similarly, in biometrics, entropy-driven texture analysis has shown promise in enhancing the accuracy of fingerprint, iris, and face recognition systems by capturing fine-grained structural variations. Integrating entropy measures with deep learning and hybrid feature fusion approaches could further expand their impact, especially in radiomics and automated diagnostics.

By addressing these gaps, future research can enhance methodological robustness and broaden the scope of entropy-based texture analysis, ensuring its continued relevance in rapidly evolving technological domains. Future research should focus on improving entropy-based methods by integrating deep learning techniques, optimizing computational frameworks, and developing standardized benchmarks for texture classification. The increasing use of entropy in radiomics suggests potential for further exploration in automated diagnostics. Additionally, expanding entropy applications beyond medical imaging into remote sensing, industrial quality control, and biometrics can offer new avenues for research. Strengthening interdisciplinary collaborations will be crucial in advancing entropy-driven texture analysis and ensuring its relevance in emerging technological landscapes.

ACKNOWLEDGMENT

The author gratefully acknowledges the Postgraduate Management Center of Universiti Malaysia Terengganu for organizing a resourceful workshop on bibliometric analysis, which provided valuable guidance and tools that enabled the successful completion of this work.

DECLARATION OF GENERATIVE AI IN SCIENTIFIC WRITING

Generative AI tools were used solely to improve the readability and language of this manuscript. All AI-assisted editing was conducted under human control. The authors take full responsibility for the content of this work. No AI tools were involved in the conceptualization, analysis, interpretation of results, or drafting of scientific content. In accordance with ethical guidelines, no AI tools are listed as authors or co-authors.

CREDIT AUTHORS' STATEMENT

Muqaddas Abid: Conceptualization; Methodology; Software; Writing - Original draft preparation. Muhammad Suzuri bin Hitam: Supervision; Validation; Writing - Reviewing and Editing; Funding acquisition. Rozniza Ali: Supervision; Validation; Funding acquisition. Muhammad Hammad: Methodology; Software; Formal Analysis; Writing - Original draft preparation.

REFERENCES

[1] A. Humeau-Heurtier, "Color texture analysis: A survey," IEEE Access, vol. 10, pp. 107993–108003, 2022.

[2] Y. Liu, W.-C. Lin, and J. Hays, "Near-regular texture analysis and manipulation," ACM Trans. Graph., vol. 23, no. 3, pp. 368–376, 2004.

[3] B. J. Balas, "Texture synthesis and perception: Using computational models to study texture representations in the human visual system," Vision Res., vol. 46, no. 3, pp. 299–309, 2006.

[4] L. Armi and S. F. Ershad, "Texture image analysis and texture classification methods—A review," CoRR, abs/1904.06554, 2019.

[5] M. K. Ghalati, A. Nunes, H. Ferreira, P. Serranho, and R. Bernardes, "Texture analysis and its applications in biomedical imaging: A survey," IEEE Rev. Biomed. Eng., vol. 15, pp. 222–246, 2021.

[6] C. E. Shannon and W. Weaver, A Mathematical Model of Communication, Urbana, IL: Univ. Illinois Press, 1949, pp. 11–20.

[7] S. M. Pincus, "Approximate entropy as a measure of system complexity," Proc. Natl. Acad. Sci. USA, vol. 88, no. 6, pp. 2297–2301, 1991.

[8] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," Am. J. Physiol. Heart Circ. Physiol., vol. 278, no. 6, pp. H2039–H2049, 2000.

[9] C. Bandt and B. Pompe, "Permutation entropy: A natural complexity measure for time series," Phys. Rev. Lett., vol. 88, p. 174102, Apr. 2002.

[10] M. Rostaghi and H. Azami, "Dispersion entropy: A measure for time-series analysis," IEEE Signal Process. Lett., vol. 23, no. 5, pp. 610–614, 2016.

[11] P. Li, C. Liu, K. Li, D. Zheng, C. Liu, and Y. Hou, "Assessing the complexity of short-term heartbeat interval series by distribution entropy," Med. Biol. Eng. Comput., vol. 53, pp. 77–87, 2015.

[12] X. Liu, A. Jiang, N. Xu, and J. Xue, "Increment entropy as a measure of complexity for time series," Entropy, vol. 18, 2016.

[13] M. Costa, A. L. Goldberger, and C.-K. Peng, "Multiscale entropy analysis of complex physiologic time series," Phys. Rev. Lett., vol. 89, no. 6, p. 068102, 2002.

[14] B. García-Martínez, A. Fernández-Caballero, R. Alcaraz, and A. Martínez-Rodrigo, "Application of dispersion entropy for the detection of emotions with electroencephalographic signals," IEEE Trans. Cogn. Develop. Syst., vol. 14, no. 3, pp. 1179–1187, 2021.

[15] L. Guzmán-Vargas, A. Zabaleta-Ortega, and A. Guzmán-Sáenz, "Simplicial complex entropy for time series analysis," Sci. Rep., vol. 13, no. 1, p. 22696, 2023.

[16] G. Li, Y. Han, and H. Yang, "A new underwater acoustic signal denoising method based on modified uniform phase empirical mode decomposition, hierarchical amplitude-aware permutation entropy, and optimized improved wavelet threshold denoising," Ocean Eng., vol. 293, p. 116629, 2024.

[17] L. E. V. Silva, A. C. S. Senra Filho, V. P. S. Fazan, J. C. Felipe, and L. M. Junior, "Two-dimensional sample entropy: Assessing image texture through irregularity," Biomed. Phys. Eng. Express, vol. 2, no. 4, p. 045002, 2016.

[18] S. M. Pincus and R. R. Viscarello, "Approximate entropy: A regularity measure for fetal heart rate analysis," Obstet. Gynecol., vol. 79, no. 2, pp. 249–255, 1992.

[19] H. Azami, L. E. V. da Silva, A. C. M. Omoto, and A. Humeau-Heurtier, "Two-dimensional dispersion entropy: An information-theoretic method for irregularity analysis of images," Signal Process. Image Commun., vol. 75, pp. 178–187, 2019.

[20] H. Azami, J. Escudero, and A. Humeau-Heurtier, "Bidimensional distribution entropy to analyze the irregularity of small-sized textures," IEEE Signal Process. Lett., vol. 24, no. 9, pp. 1338–1342, 2017.

[21] M. Hilal, C. Berthin, L. Martin, H. Azami, and A. Humeau-Heurtier, "Bidimensional multiscale fuzzy entropy and its application to pseudoxanthoma elasticum," IEEE Trans. Biomed. Eng., vol. 67, no. 7, pp. 2015–2022, 2019.

[22] M. Abid, M. S. Hitam, R. Ali, H. Azami, and A. Humeau-Heurtier, "Bidimensional increment entropy for texture analysis: Theoretical validation and application to colon cancer images," Entropy, vol. 27, no. 1, p. 80, 2025.

[23] A. S. Gaudêncio, M. Hilal, J. M. Cardoso, A. Humeau-Heurtier, and P. G. Vaz, "Texture analysis using two-dimensional permutation entropy and amplitude-aware permutation entropy," Pattern Recognit. Lett., vol. 159, pp. 150–156, 2022.

[24] W. Li, Y. Zhao, Q. Wang, and J. Zhou, "Twenty years of entropy research: A bibliometric overview," Entropy, vol. 21, no. 7, p. 694, 2019.

[25] W. H. Lam, W. S. Lam, S. H. Jaaman, and P. F. Lee, "Bibliometric analysis of information theoretic studies," Entropy, vol. 24, no. 10, p. 1359, 2022.

[26] N. J. Van Eck and L. Waltman, "Citation-based clustering of publications using CitNetExplorer and VOSviewer," Scientometrics, vol. 111, pp. 1053–1070, 2017.

[27] N. Pakniyat, J. Abdullah, O. Krejcar, and H. Namazi, "Complexity-based analysis in biomedical image analysis: A review," Fractals, vol. 32, no. 6, p. 2430002, 2024.

[28] T. Akram, A. Alsuhaibani, M. A. Khan, S. U. Khan, S. R. Naqvi, and M. Bilal, "Dermo-optimizer: Skin lesion classification using information-theoretic deep feature fusion and entropy-controlled binary bat optimization," Int. J. Imaging Syst. Technol., vol. 34, no. 5, p. e23172, 2024.

[29] M. Abid, M. S. Hitam, R. Ali, H. Azami, and A. Humeau-Heurtier, "Spatio-frequency texture analysis using wavelet increment entropy: Methodology and application to MRI in multiple sclerosis," Inf. Sci., p. 122669, 2025.

[30] J. Mahmoodi, D. Abbasi-Moghadam, A. Sharifi, H. Nezamabadipour, M. Esmaeili, and A. Vafaeinejad, "Dessa-net model: Hyperspectral image classification using an entropy filter with spatial and spectral attention modules on deepnet," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., 2024.

[31] Y. Hua, X. Xi, C. Qu, J. Du, M. Weng, and B. Ye, "An adaptive watermarking for remote sensing images based on maximum entropy and discrete wavelet transformation," KSII Trans. Internet Inf. Syst., vol. 18, no. 1, pp. 192–210, 2024.

[32] S. Agarwal and K.-H. Jung, "Digital image steganalysis using entropy-driven deep neural network," J. Inf. Secur. Appl., vol. 84, p. 103799, 2024.

[33] A. A. Saddek, T.-K. Lin, Y.-T. Lin, and K.-W. Kuo, "Enhancing the credibility of an entropy-based structural health monitoring system using convolutional neural networks," J. Civil Struct. Health Monit., pp. 1–17, 2025.

[34] F. Abdollahi-Mamoudan, C. Ibarra-Castanedo, and X. P. V. Maldague, "Non-destructive testing and evaluation of hybrid and advanced structures: A comprehensive review of methods, applications, and emerging trends," Sensors, vol. 25, no. 12, p. 3635, 2025.

[35] K. An, C. Li, G. Long, and J. Ding, "An improved entropy regularization method for defect detection in multi-layer composites," IEEE Trans. Antennas Propag., 2024.

[36] F. Ng, B. Ganeshan, R. Kozarski, K. A. Miles, and V. Goh, "Assessment of primary colorectal cancer heterogeneity by using whole-tumor texture analysis: Contrast-enhanced CT texture as a biomarker of 5-year survival," Radiology, vol. 266, no. 1, pp. 177–184, 2013.

[37] A. Wibmer, H. Hricak, T. Gondo, K. Matsumoto, H. Veeraraghavan, D. Fehr, J. Zheng, D. Goldman, C. Moskowitz, S. W. Fine, et al., "Haralick texture analysis of prostate MRI: Utility for differentiating noncancerous prostate from prostate cancer and differentiating prostate cancers with different Gleason scores," Eur. Radiol., vol. 25, pp. 2840–2850, 2015.

[38] V. Goh, B. Ganeshan, P. Nathan, J. K. Juttla, A. Vinayan, and K. A. Miles, "Assessment of response to tyrosine kinase inhibitors in metastatic renal cell cancer: CT texture as a predictive biomarker," Radiology, vol. 261, no. 1, pp. 165–171, 2011.

[39] F. Ng, R. Kozarski, B. Ganeshan, and V. Goh, "Assessment of tumor heterogeneity by CT texture analysis: Can the largest cross-sectional area be used as an alternative to whole tumor analysis?" Eur. J. Radiol., vol. 82, no. 2, pp. 342–348, 2013.

[40] F. Tixier, M. Hatt, C. C. Le Rest, A. Le Pogam, L. Corcos, and D. Visvikis, "Reproducibility of tumor uptake heterogeneity characterization through textural feature analysis in 18F-FDG PET," J. Nucl. Med., vol. 53, no. 5, pp. 693–700, 2012.

[41] B. Ganeshan, K. Skogen, I. Pressney, D. Coutroubis, and K. Miles, "Tumour heterogeneity in oesophageal cancer assessed by CT texture analysis: Preliminary evidence of an association with tumour metabolism, stage, and survival," Clin. Radiol., vol. 67, no. 2, pp. 157–164, 2012.

[42] B. Ganeshan, S. Abaleke, R. C. D. Young, C. R. Chatwin, and K. A. Miles, "Texture analysis of non-small cell lung cancer on unenhanced computed tomography: Initial evidence for a relationship with tumour glucose metabolism and stage," Cancer Imaging, vol. 10, no. 1, p. 137, 2010.

[43] M. Hall-Beyer, "Practical guidelines for choosing GLCM textures to use in landscape classification tasks over a range of moderate spatial scales," Int. J. Remote Sens., vol. 38, no. 5, pp. 1312–1338, 2017.

[44] T. Hodgdon, M. D. F. McInnes, N. Schieda, T. A. Flood, L. Lamb, and R. E. Thornhill, "Can quantitative CT texture analysis be used to differentiate fat-poor renal angiomyolipoma from renal cell carcinoma on unenhanced CT images?" Radiology, vol. 276, no. 3, pp. 787–796, 2015.

[45] M. G. Lubner, N. Stabo, S. J. Lubner, A. Munoz Del Rio, C. Song, R. B. Halberg, and P. J. Pickhardt, "CT textural analysis of hepatic metastatic colorectal cancer: Pre-treatment tumor heterogeneity correlates with pathology and clinical outcomes," Abdom. Imaging, vol. 40, pp. 2331–2347, 2015.

[46] R. M. Haralick, K. Shanmugam, and I. H. Dinstein, "Textural features for image classification," IEEE Trans. Syst. Man Cybern., no. 6, pp. 610–621, 1973.

[47] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," Pattern Recognit., vol. 29, no. 1, pp. 51–59, 1996.

[48] A. K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters," Pattern Recognit., vol. 24, no. 12, pp. 1167–1186, 1991.