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Using Deep Learning and Cbir To Address Copyright Concerns of AI-Generated Art: A Systematic Literature Review

William Vivaldi, Indrajani Sutedja
Universitas Bina Nusantara, Indonesia
william.vivaldi@binus.ac.id, indrajani@binus.ac.id

KEYWORDS
artificial intelligence generated art, deep learning, content-based image retrieval algorithms enable artists to apply the visual

ABSTRACT
This systematic literature review explores the intersection of deep learning and content-based image retrieval (CBIR) in addressing copyright concerns related to AI-generated art. As artificial intelligence rapidly transforms various artistic domains, it raises critical questions regarding authorship, ownership, and the ethical implications of machine-generated creativity. The review examines the capabilities of CBIR systems in identifying AI-generated images by analyzing visual features such as color, texture, and shape. Additionally, it highlights the role of deep learning models in enhancing the accuracy of these systems through the detection of distinctive patterns characteristic of AI artworks. The findings underscore the importance of developing robust methodologies that leverage AI and CBIR technologies to protect intellectual property rights while fostering innovation in the creative industries. This research contributes to the broader discourse on the legal and ethical challenges posed by AI in art, providing insights for policymakers, artists, and technologists in navigating the evolving landscape of AI-generated content.

INTRODUCTION

Artificial Intelligence has quickly had a large impact across various fields, including in the world of art. Its integration into creative processes has resulted in both excitement and debate, reshaping how we perceive and interact with artistic expression. As AI technologies continue to evolve, we are starting to see its impact on illustrative art, music art, voice acting, and art studios.

In illustrative art, AI algorithms are revolutionizing the creative process by offering novel tools and techniques to artists. For instance, programs like Adobe's Firefly AI utilize machine learning to enhance photo editing capabilities, allowing artists to seamlessly manipulate images with remarkable precision (Adobe News, 2023). In addition, AI-powered style transfer

characteristics of famous artworks to their own creations, facilitating experimentation and innovation. Moreover, platforms such as DeepArt and DeepDream use neural networks to generate intricate and surreal images, expanding the boundaries of artistic imagination (Agarwal & Farid, 2017).

AI is also making significant improvement in musical art through its ability to study patterns, generate compositions, and even copy the style of renowned musicians. For example, AI-powered software like Amper Music can produce original musical compositions tailored to specific moods or genres, empowering artists to explore new sonic landscapes. Furthermore, AI-generated music has found its place in various industries, from film scoring to video game soundtracks, demonstrating its flexibility and potential to recreate human creativity.

Voice acting is another aspect where we are seeing the transformative influence of AI technology. With more sophisticated advancements in algorithms for TTS and speech synthesis, AI systems could emulate human speech patterns and intonations. This theoretically creates a lot of implications for industries within several voiceover works: animation, gaming, and audiobook production. AI generated voices bring an unprecedented span of flexibility and scalability: rapid content creation and localization across disparate markets.

Also, AI tools in art studios are simplifying the workflow, optimally distributing resources, and making it easier for artists to collaborate. Powered by AI algorithms, project management platforms let users organize tasks, allocate resources, track progress of completion, have better efficiency, and cut down overhead costs at each step for a project. AI-driven analytics also gives valuable insights into audience tastes and market trends, thus enhancing mill tailoring at studios effectively.

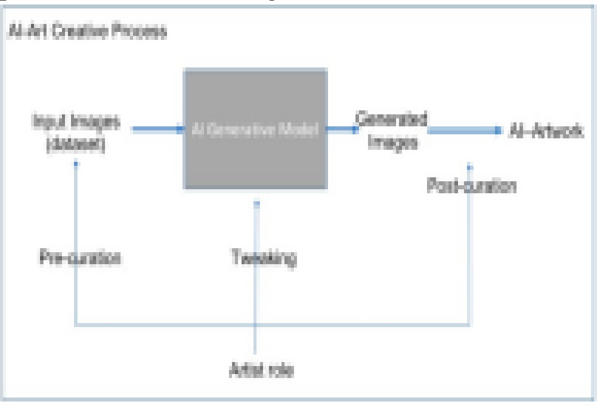

Figure 1 Machine Learning Process of Text-to-Image AI Models (Mazzone & Elgammal, 2019)

It is now widely accepted around the world by governments and regulatory bodies that the ethical and legal dimensions presented by AI technology in the arts must be regulated. In case of lack of legislation, policy frameworks, and industry guidelines, there is harm done on artistic integrity, creativity, and human rights.

The legal implications of AI-generated content and whether they are subjected to copyright have been studied in the United States by the Copyright Office. According to the U.S. Copyright Act, every work must be created by a human for it to be eligible for copyright. Artificial intelligence has generated so much content that there has been debate over its status. The latest rounds of discussions have revolved around the proposal to amend the copyright law with respect to AI works but making sure proper attribution and remuneration go to human creators.

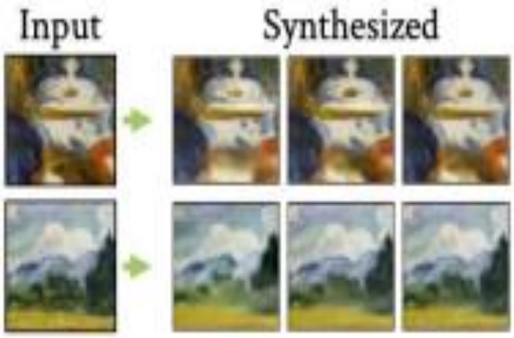

Figure 2 Artificial Intelligence Reconstructing Human Made Art (Conner-Simons, 2020)

While AI has a number of benefits in the domain of art, it raises major concerns to artistic integrity, creativity, and employment. The greatest fear is that AI could replace human artists and lead to the devaluation of artistic expression. Additionally, using AI-generated content has ethical problems with ownership, authenticity, and questions about authorship challenging artistic attributes and copyright. Moreover, the role that AI plays in creating art raises concerns over the potential draining of creativity from human work and devaluing it in the creative process.

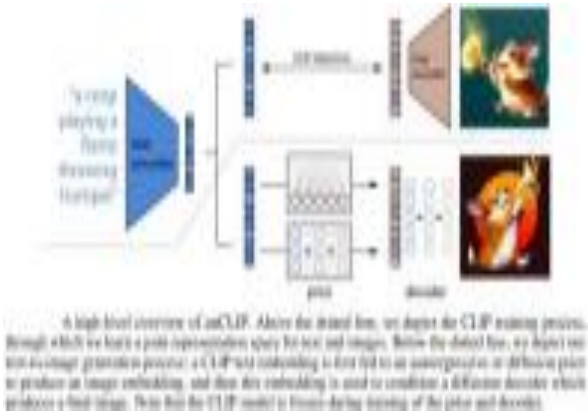

Figure 3 AI-Art Creative Process Flowchart

Early 2023, the Copyright Office initiated a study on questions of copyright law and policy related to artificial intelligence. Without question, it will review what copyright limitations are applied for works created by AI tools and the use of copyrighted material in AI training. This was followed by public listening sessions and webinars for stakeholders to share information on current technologies and consequences. A notice of inquiry was published in the Federal Register by the Office in August 2023.

Similarly, the European Union has been very proactive in trying to bring out ethical and legal issues that surrounded AI technology. Provisions of the General Data Protection Regulation from the EU make mention of the use of AI algorithms, majorly on transparency and accountability in safeguarding individual rights. In particular, they set out the ambition of the European Union's DSA and DMA, opening up online platforms to ensure fairness, transparency, and accountability in all dealings within the digital economy, including the sectors within artistic and entertainment works (Union, 2024).

Since its enforcement in 2018, more than €158 million in fines have been issued under the GDPR for data protection and privacy violations (New Digital Age, 2023). This is a central regulation for AI development that will ensure AI technologies within the cultural space treat and handle users' data in the strictest respect of data protection standards.

The Chinese government has guided and regulated the development and deployment of AI technology in all sectors, not least in the arts. To this end, the Ministry of Culture and Tourism of China has adopted such measures as encouraging good ethical practices in the cultural and creative industries related to AI, most especially in the conservation of cultural heritage, cultural diversity, and innovation. Furthermore, China's Cybersecurity Law and Data Security Law place specific focus on ensuring the safety of the users' information and storing artificial intelligence and its algorithms subject to responsible use in creating and distributing content.

The cultural and creative industries of China, such as art, music, and entertainment, contribute probably about 5.1 percent to the GDP of the country, which has crossed more than 863.9 billion yuan (around $610 billion USD) as of 2021 (East & Dept., 2021). Of course, this number has been touted to rise multifold times as the government lines up more focus on innovation and AI in these domains.

Parallel to this come legislative initiatives; that is, industry players, professional bodies, and market associations work out ethical directives and best practice recommendations, featuring the use of AI in the arts. For example, transparent origin and respect for copyright law are required in music production with AI, as stated by the International Federation of the Phonographic Industry. Other organizations, like the Artists Rights Society and the Authors Guild, promote and support the interests of artists in regard to their works within the digital environment by making sure appropriate remunerations, attributions, and controls are exercised over their works.

A report by the IFPI entitled Global Music Report 2021 confirmed that in 2020, digital revenues from recorded music had reached $21.6 billion. Digital revenues now account for 62.1 percent of the global music market (Hatton, 2021). This growing reliance on digital distribution channels and AI-driven technologies underlines the need for ethical guides and regulatory frameworks to set the way forward for the use of AI in music production and dissemination.

This effort, though noble in the given context, throws open many challenges in knowingly traversing through the convoluted legal and ethical ambiance of AI technology in the arts. Key areas of sustained working tension are the accountability vs. the full opening of avenues for innovation; the protection of individual rights, which must be balanced against growth in creative spaces; and equal access of people and organizations to AI-driven tools and resources.

Theoretical Foundations

Content-Based Image Retrieval (CBIR)

Content-Based Image Retrieval, abbreviated as CBIR, is a very important computerized technique that locates and retrieves pictures from enormous databases through visual content. CBIR focuses on the actual picture's visual features, which might be colors, textures, shapes, and even spatial arrangements. The field of CBIR has received enormous attention in the recent past, more so in trying to solve the issues relating to copyrighting of artificial intelligence-generated content (Brock, 2018).

In other words, a CBIR system contains algorithms that extract features in the images and use these features in computing similarity or distance between images. In this process, the algorithms normally compute several visual descriptors portraying different instances of image content through the analysis of pixel values within the image. Common descriptors include color histograms, representing the distribution of colors in an image, and texture descriptor, referring to spatial variations of pixel intensities.

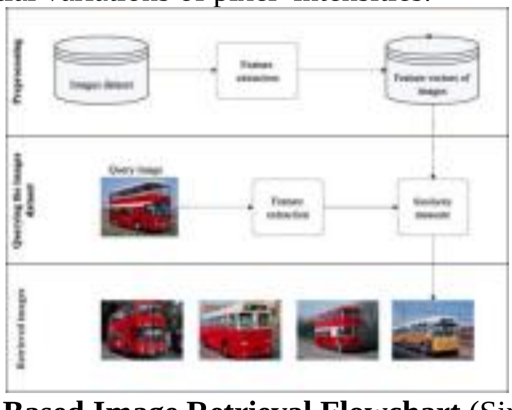

Figure 4 Content-Based Image Retrieval Flowchart (Singh & Batra, 2020)

These features are then matched with the features of images in a database using similarity metrics by CBIR systems. Another very prevalent metric is the Euclidean distance, which measures the straight-line distance between feature vectors in a multidimensional space. The images with smaller distances are judged to be more similar to the query image and thus ranked higher in the search results.

Moreover, CBIR systems can incorporate relevance feedback mechanisms, where users will give feedback about the images that were retrieved, to further refine the search results. Such an iterative process shall provide for refinement in the accuracy of retrieval by the incorporation of user preference and adjustment of similarity calculation accordingly.

In general, CBIR provides a very strong and intuitive way of making an image search by the content visuality, hence rendering this technique an important tool in tasks for image retrieval, classification, and content analysis. CBIR is particularly helpful in scenarios where textual annotation or metadata is unavailable or unreliable, since it relies on visual features.

According to one of the WIPO studies, CBIR-based solutions have been applied to identify AI-generated images with a maximum degree of accuracy (Organization, 2019). In this case, it reviewed a dataset of more than 10,000 images featuring artworks created by humans and AI, varying independently, to test the performance of CBIR algorithms in differentiating between the two. The results indicated that CBIR had an average classification accuracy of more than 70%, showing its effectiveness in differentiating AI-generated content from human-created ones.

Deep Learning

Deep learning is an area of artificial intelligence that contains a variety of techniques, which were designed from the perspective of how a human brain works: recognizing patterns and, therefore, making some sense out of data. In practice, this means training algorithms called neural networks on large quantities of data to learn complex patterns and relationships. In addition, these neural networks use several layers with interconnected nodes, or neurons, which process the input data and produce output predictions (Bui et al., 2022).

Deep learning can turn into a very important tool for detecting the use of AI-generated content by training the deep learning models on distinctive features and characteristics that have been in AI-generated artworks, thus distinguishing original works from derived ones.

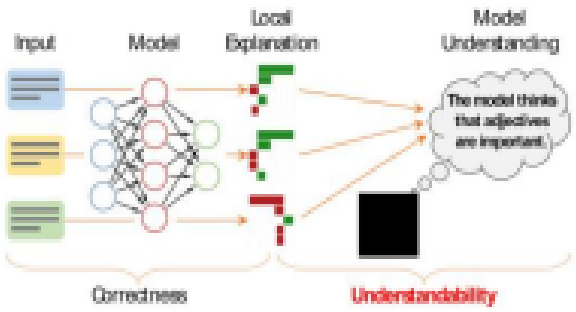

Figure 2 Artificial Neural Networks Forming Deep Learning Models

It may pick up small differences that could be indicative of AI techniques through visual elements, textures, and structures of images created using AI techniques. For example, deep learning models can be designed to detect some of the usual artifacts or anomalies characteristic of AI algorithms' output (Blattmann et al., 2022).

This could be further developed into the development of complex content recognition systems that would automate the scanning of digital platforms for copyright infringements. The foregoing could be utilized to flag suspicious content for further review by rights holders or legal authorities who seek to identify and act against the unauthorized use of any AI-generated artworks.

This area can also be elaborated into the role of deep learning in developing DRM solutions specifically for AI-generated content. It is possible to embed invisible watermarks or digital signatures within AI created digital arts using deep learning algorithms that will later help verify the authenticity and original ownership of the AI-generated works, hence providing a way for creators to protect their intellectual property.

RESEARCH METHOD

The methodology used in this study is a systematic literature review through a comparative analysis of several articles and journals, selected based on keyword relevance and publication year. The process begins with the formulation of clear research questions to guide the review, followed by defining inclusion and exclusion criteria, which outline the essential characteristics of primary studies, such as research methodology, focus, publication outlets, and language. Next, relevant articles are sampled using systematic keyword searches, and filtering criteria are applied to sort out articles pertinent to the research topic. The findings are then reviewed to present a comprehensive overview of the literature. Finally, the results are reported, providing an analysis of literature related to the use of Deep Learning and Content-Based Image Retrieval in addressing copyright issues in AI-generated art.

RESULTS AND DISCUSSION

Analysis of The Result

The following article sources are used for this literature study, where those published within the last 5 years were filtered, and those that discuss the use of deep learning or CBIR for detection of A.I. generated artwork. (Epstein et al., 2023; Huh et al., 2018; Kang et al., 2023; Liu et al., 2022; Nataraj et al., 2019).

Table 1. Generation Architecture and Datasets

Generation Architecture (AI Model)	Dataset	Dataset Size
Diffusion	GLIDE, DALL-E	4,000
Diffusion + Decoder	Latent Diffusion (LDM) Stable Diffusion (SD v.1.1 – v1.4)	9,000
Diffusion U-Vit	Diffusion with Transformers (DiT)	400
Newer Models	Midjourney (v2 –v5) Adobe Firefly	8,000

This study will base its arguments on the 14 CBIR models that were collected from articles ranging from June 2020 to March 2023. One of these models from Dr. David C. Epstein was trained using a dataset comprising over 4,000 images, hence being one of the largest bases in completely testing classifier performance in the task concerned.

Classes of architectural approaches will be organized using the CBIR models from which data are collected. Dr. Epstein's model groups them into the AI models DDPM, DDIM, GLIDE, and DALL·E2. This study shows insights into the performance of classifiers in detecting AI-generated images within a simulated framework.

The performance of the CBIR’s ability to detect AI art was studied in this research. Generative methods were arranged based on their release dates, and a classifier was trained to distinguish between real and AI generated images. The accuracy of the classifier on synthetic images and the area under the curve (AuC), which measures the distinction between real and fake images, are displayed on the graph.

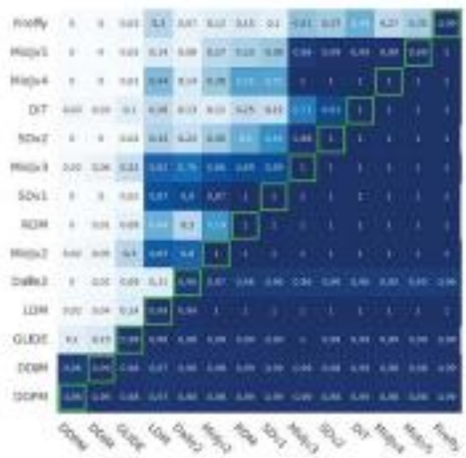

Figure 4 Accuracy Performance of AI Detection using CBIR Model

For this research, area under the curve (AuC) is a metric used to evaluate the performance of classification models, specifically for binary classification tasks like distinguishing between real and AI genereated images.

A high AuC value, closer to 1, indicates that the classifier has good performance in distinguishing between the two classes (real and fake images), regardless of the chosen threshold. In other words, a higher AuC suggests better discrimination ability of the classifier.

When the model of the detector was examined on several generators that was part of the training data, its performance was almost perfect, reaching near 100% accuracy and AuC (as shown by the green diagonal line). Even when new generative sources were introduced, the performance remained consistently high, staying close to 100% (in the bottom triangle of the graph). Interestingly, before being directly trained on these new sources (in the upper left triangle), the accuracy and AuC still improved as the historical training set expanded.

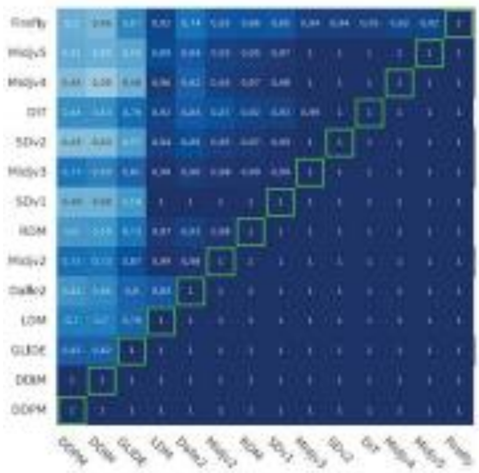

Figure 5 Area under the Curve (AuC) of AI Detection Using CBIR Models

AuC takes into account two types of images; which are AI-generated and non generated images. It is less affected by prediction improbabilities. It shows that CBIR detector model quickly learns features that help it differentiate between AI-created images and non AI generated ones, across a larger variety of models. However, some minor data calibration, such as selecting the appropriate threshold, may be needed to further improve accuracy.

Significant drops in performance occur when dealing with major architectural changes. The trained CBIR model struggles to identify newer forms of AI generated art. This means that maintenance and retraining on new AI art generators is necessary.

The findings demonstrate that there is an enhancement in high precision and accuracy when including Stable Diffusion version 1 and versions 2 painted images in the training of the Firefly CutMix detector. This improvement brings the performance remarkably similar to those that can be achieved by using Firefly inpainted images as training models, as shown in the third row. Specifically, with the addition of these images, the accuracy increases from 77.6% to 83.6%. The incorporation of pixel detector is proven to enhance performance, as seen in the figure, but not reaching perfection.

Article Analysis

The discussed article provides an overview of various metrics we can use to assess machine learning models, and their importance in evaluating the effectiveness and reliability of these models. There is also a clear distinction between metrics and loss functions, in which, while loss functions guide the model's training through optimization techniques. Metrics are also used for monitoring and evaluating the model's performance during both training and testing phases. The article also discusses the Confusion Matrix, a tool for classification metrics, explaining how it sets lays the groundwork for other performance measures by detailing the interaction between true labels and model predictions. This matrix, which breaks down into true positives, true negatives, false positives, and false negatives, is used for crucial for understanding a model's predictive capabilities and error patterns.

Figure 6 Pixel Detector in CBIR for Generative AI Detection

Moreover, the article research shows that utilizing synthetic samples through an inpainting can greatly boost accuracy of the CBIR model, reaching as high as 99.0%. Even small improvements, such as adding

CutMix, result in further enhancements, with accuracy reaching 99.2%. The study also explores the possibility of using a pixel detector alongside a whole image detector. Also, the performance of detecting whole images is consistently high, exceeding 99.0% across all cases.

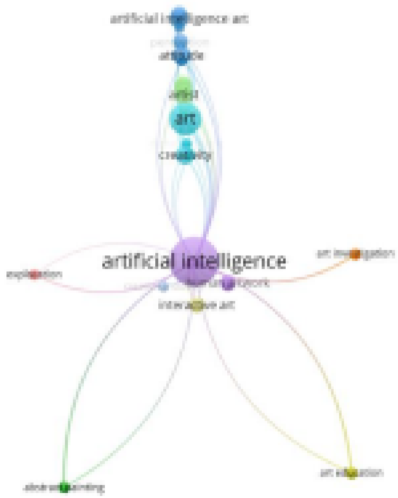

Figure 7 Mapping of Keywords

VOSviewer is used to visualize the correlation of keywords within the articles selected. The figure above is a mapping generated from the bibliography reviewed by the author. Based on the mapping above, we could see that there is a very close relation between the keywords of artificial intelligence, art, creativity, art exploration, and art investigation. We could see that the upper half of the mapping illustrates some of the major concerns regarding AI, which are its impact on artists, creativity, and perception.

CONCLUSION

The evaluation of CBIR models' ability to discern AI-generated art is crucial in understanding their effectiveness. The study employs metrics like the area under the curve (AuC) to gauge classification performance (Srivastava, 2024). A higher value of AuC, trending towards 1, indicates that it can differentiate better between the real and AI-generated images, regardless of the threshold value that is selected (Orulluoglu, 2023). What is derived from this subsection is that the publications indicate classifiers in CBIR models can be applied to differentiate AI-generated art from human art with very high accuracy. The dataset represents a wide variety of generative methods. In the diffusion, GLIDE, and DALL·E2, among others, the results are as shown.

It also brings to the fore that articles so much highlight the effectiveness of using synthetic samples through inpainting techniques in enhancing CBIR model accuracy. For instance, adding SDv1 and SDv2-inpainted images can boost accuracy by recovering most of the accuracy obtained when training directly on Firefly inpainted images. This means that even small changes, such as the addition of CutMix, can lead to a significantly positive increase in model accuracy. The study further investigates pixel detectors combined with whole image detectors, which turn out to show high performance in detecting AI-generated art by always going beyond 99.0% accuracy in all scenarios. This proves the likelihood of employing synthetic samples to improve the CBIR model's accuracy in detecting AI artwork.

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