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Image Error Detection: A Systematic Literature Review

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ABSTRAK

Kemajuan teknologi, serta penciptaan teknik dan metodologi baru untuk analisis gambar, berlangsung cepat. Namun bisa terjadi kesalahan deteksi pada gambar. Kesalahan deteksi gambar akan dibahas dalam tinjauan literatur yang sistematis. Studi ini mencoba untuk mempelajari tentang jenis gambar yang digunakan, teknik yang sering digunakan, dan metrik yang digunakan untuk menguji kebenaran dari pendekatan yang disarankan. Jenis gambar yang paling sering digunakan adalah gambar medis seperti *Magnetic Resonance Imaging*, algoritma yang banyak digunakan adalah algoritma berbasis *Convolutional Neural Networks*. Metode yang banyak digunakan adalah metode berbasis machine learning, dan pengukuran yang banyak digunakan adalah metode pengukuran *Peak Signal Noise Ratio* untuk mengukur akurasi algoritma.

Kata Kunci:

Kesalahan deteksi gambar, Teknologi deteksi gambar, Tinjauan Literatur Sistematis

***Keywords* :**

Image detection technology, Image detection error, Systematic Literature Reviews

ABSTRACT

The advancement of technology, as well as the creation of new techniques and methodologies for image analysis, is rapid. However, image detection may face some errors. Image error detection will be discussed in this comprehensive literature review. Throughout the papers, this work attempts to learn about the types of images used, algorithms that are frequently used, techniques that are frequently used, and metrics used to test the correctness of the suggested approach. The most commonly used image type is medical images such as Magnetic Resonance Imaging, the algorithm that is widely used is a Convolutional Neural Networks based algorithm. The method that is widely used is a machine learning-based method, and the measurement that is widely used is a Peak Signal Noise Ratio measurement method to measure the accuracy of the algorithm.

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INTRODUCTION

Image detection technology has additional applications. It will be useful for anything from just login into your smartphone to detecting cancer with your eyes to autonomous driving (Willis & Hasan, 2020) or recognizing Japanese Characters (Hidayat & Iswari, 2018). In medicine, MRI

(Magnetic Resonance Imaging) image detection can aid in the early detection of illness. Early diagnosis can sometimes save a patient's life in the medical industry. Images may be detected using a variety of techniques, methodologies, and systems. However, somehow the image is falsely detected. A thorough literature study is conducted to examine all accessible publications or research on image error detection. Systematic literature reviews, also known as systematic reviews, seek to locate, assess, and interpret every study and research finding relating to a certain research subject, topic area, or phenomenon of interest. This systematic review is conducted for a variety of purposes, including summarizing the available evidence for therapy or technology. Using a particular brief, and summarizing empirical evidence on the benefits and limits of certain strategies. Identifying gaps in a present study and suggesting opportunities for future study or inquiry, as well as providing a framework/background for correctly positioning new research initiatives.

METHODS

According to Kitchenham's Guidelines for Performing Systematic Literature Reviews in Software Engineering Version 2.3 (Kitchenham & Charters, 2007), the steps in completing a Systematic Literature review are as follows: planning, conducting the review, and reporting the review. The first step is to plan for a systematic review which includes identifying needs, creating criteria and procedures, as well as evaluating criteria and reports. After determining the three stages the next planning is conducting the review. The followings are the 6 stages of conducting the review consisting of research questions, search strategy, study selection criteria, quality assessment criteria, data extraction and monitoring, and data synthesis.

Research questions (RQ) aim to identify studies that are relevant to the research topic. In this study, several research questions have been defined in the context of image error detection as shown in Table 1. In a systematic literature review, selecting and choosing research topics is a critical stage. The importance of research questions in establishing and determining the overall study aims cannot be overstated.

Table 1. Research Questions

No.	Research Questions	Objectives
RQ1	What type of data/image is used to detect image errors?	Know what type of image to use for image error detection
RQ2	What algorithms are often used to detect image errors?	Describe the variations in the category of algorithms used for image error detection
RQ3	What is the framework/method for detecting image errors?	Identify the classification framework for the image error detection
RQ4	What measurement methods are used to measure the results of image error detection?	Find methods are most often used to measure image error detection

Search strategy (SS) establishes a search strategy to find as many primary studies as possible related to image error detection. All journals were obtained through IEEEXplore. The search was carried out using the keywords: image error type with filter: journal, open access only with the year range: 2019-2022. Resulting in a total of 160 journals. The duration of the journal search was conducted from Apr 11, 2022, to Apr 24, 2022, using 50 journals out of 160 journals. 12 journals are starting in 2019, 19 in 2020, and 19 in 2021, out of the total 50 chosen journals.

Study Selection Criteria (SSC) determines the criteria for the study or journal that will be used in the review. Such as year, language, and publication. Three criteria were determined to select suitable journals for systematic literature review. First, the search term is partly included in the title, abstract, or keywords. Second, study topics regarding image error detection that do not have search terms in the sections mentioned in the previous criteria are still included if the search terms are found in other parts of the journal. Third, the results of journal research must be explained clearly and transparently based on empirical evidence. In addition, several exclusion criteria were also made to pass irrelevant studies. First, journals that are not written in English. Second, journals whose topics do not match the image error detection. Third, journals whose research methods do not use algorithms or other technical methods. Forth, journals that use video as research objects.

Quality Assessment Criteria (QAC) assesses the quality of studies and journals that meet the criteria, ensuring that the results of the journals and studies to be used are unbiased. Assessing the quality of the evidence in a systematic literature review is as important as analyzing the data in the journal. Results from studies of poor quality may confound results from studies of the literature, so the methodology must be interpreted with caution. According to Kitchenham (Kitchenham & Charters, 2007), there is no definite and universally agreed definition of the "quality" of journals. However, according to the CRD guidelines and the Cochrane Reviewers Handbook (Khan et al., 2001), both suggest that the quality of a study can be judged by whether the study minimizes bias and maximizes internal and external validity. In addition to the above concepts, one way to assess the quality of a journal is to make a checklist that meets the needs of the research topic. In addition to making a checklist, a cross-checking approach is used to ensure the consistency of all journals found. Based on the criteria of the study selection that has been set, journals that meet the quality criteria are 41 journals, and journals that do not meet the criteria are 9 journals.

Data extraction and monitoring (DEM): determines how the required information will be extracted and documented. This phase describes the system used to extract data from journals and studies that have been collected. Author and time of publication to record the name of the author or team of writers and the time of publication. Methods and category, which record the recommended method in the journal and categorize the method. Image type and categorize the image. Measurement records the measurement used to measure the accuracy of the method used in the journal.

Data Synthesis (DS) aims to tidy up and conclude the results of a systematic review. The synthesis data aims to summarize the cooperative findings from the data extraction results which can be represented as an indication to support a definitive response to the research question. After collecting the data, the data is analyzed for further data extraction.

The final stage is Reporting the review. After completing a review of all studies and the next journal is reporting the results of a systematic literature review in a format appropriate to the distribution channel and target audience.

RESEARCH RESULT AND DISCUSSION

50 journals are collected from IEEE Xplore as shown in Table 2, and in the distribution period of the last 3 years, the specified distribution years are 2019, 2020, and 2021. With the search word "Image error type", the type of publication is "journal" and access is "open access" only" which means researchers can access the journal without having to pay. After evaluating the quality of the journals, of the 50 journals collected that met the criteria, 41 journals were collected.

Table 2. The 50 Journals

Journal No	References	Journals No.	References
[P1]	Jin, Che, & Chen (2021).	[P26]	Lee, et al. (2019).
[P2]	Bhatti, et al. (2021).	[P27]	Li, et al. (2019).
[P3]	Armas Vega et al. (2020).	[P28]	Jin, Y., & Ko, B. (2020).
[P4]	Tariq et al. (2021).	[P29]	Sun, et al. (2019).
[P5]	Li (2020).	[P30]	Jin & Hao (2020).
[P6]	Duan, Zhu, & Xiang (2020).	[P31]	Shimaponda-Nawa, et al. (2020).
[P7]	Zhang et al. (2019).	[P32]	Meuel & Ostermann (2020).
[P8]	Mason et al. (2020).	[P33]	Hoyos, Ruiz, & Chavez (2021).
[P9]	Wang et al. (2020).	[P34]	Liu, J. (2021).
[P10]	Regulski & Zieliski (2020).	[P35]	Cao et al. (2021).
[P11]	Durmus (2020).	[P36]	Kim et al. (2021).
[P12]	Bakhshipour (2021).	[P37]	Jeong et al. (2021).
[P13]	Peter et al. (2021)	[P38]	Nguyen, Vo, & Lee (2020).
[P14]	Ichim & Popescu (2020).	[P39]	Weng, Zhang, & Yang (2019).
[P15]	Song et al. (2020).	[P40]	Wang et al. (2021).
[P16]	Li et al. (2021).	[P41]	Yan, Zhang, & Su (2019).
[P17]	Kawamura et al. (2022).	[P42]	Tong et al. (2021).
[P18]	Cen et al. (2020).	[P43]	Zhai et al. (2021).
[P19]	Tang et al. (2020).	[P44]	Zhuo et al. (2021).
[P20]	Ren et al. (2021).	[P45]	Misra et al. (2021).
[P21]	Ikram et al. (2019).	[P46]	Chen et al. (2019).
[P22]	Rhee (2019).	[P47]	Chen et al. (2021).
[P23]	Li et al. (2020).	[P48]	Ando & Iida (2021).
[P24]	Li et al. (2019)	[P49]	Chen & Liu (2019).
[P25]	Molaei et al. (2021).	[P50]	Majeed & Isa (2020).

RQ1: Type of data/image used to detect image errors

The images used in the journals that have been collected have various types of images such as MRI results from the brain, modified or edited images, currency photos, and others. To facilitate data collection, the images that have been collected are re-categorized with the following conditions: images that are the result of an MRI or have a function in the medical field are categorized into 'medical images', images that are photos taken from satellites and images obtained via Google earth is categorized as a 'satellite image', an image that has gone through a digital editing process or other digital modifications and made digitally is categorized as a 'computer-generated image'. Images that do not fit into these three categories, will be categorized based on the object used in the journal. Table 3 shows all categories of the types of data used in this study. The types of data or images that are often used are images in the medical image category with a percentage of 25%. Satellite images with a percentage of 18.8%, and computer-generated images with a percentage of 16.7%. The findings, medical images are frequently utilized to detect image flaws. A medical image, as previously defined, is an image that serves a medical purpose, such as an MRI. Le Zhang et al (2019) employed CMR (cardiac magnetic resonance) imaging to monitor the left ventricle of the heart anatomy to monitor illness progression and assess patient response following surgery and treatment. Ichim and Popescu (2020) employ dermoscopic images to identify a melanoma, which is skin cancer, as another example that does not involve MRI.

Table 3. Image Types Used To Detect Image Errors

Image Types	Total	Journals No.	Percentage
Medical image	12	[P7},[P8],[P10],[P13],[P14],[P20],[P21],[P23],[P28],[P29],[P38],[P49]	25.0%
satelite image	9	[P2],[P16],[P19],[P30],[P35],[P40],[P41],[P43],[P47]	18.8%
computer-generated image	8	[P9],[P11],[P15],[P17],[P22],[P25],[P28],[P33]	16.7%
plants	4	[P1],[P12],[P18],[P45]	8.3%
human	3	[P3],[P36],[P50]	6.3%
buildings	2	[P3],[P50]	4.2%
pantograf	2	[P5],[P6]	4.2%
radar image	2	[P25],[P45]	4.2%
animals	1	[P3]	2.1%
banknotes	1	[P26]	2.1%
animals	1	[P36]	2.1%
Ancient Character	1	[P39]	2.1%
rotating disk with constant speed	1	[P48]	2.1%
Traffic scene	1	[P48]	2.1%

RQ2: Algorithm used to detect image errors

The algorithm used in the collected journals varies. One journal can use more than 1 algorithm to detect image errors. Algorithms that have CNN bases are categorized into the same as morphological-based algorithms. Algorithms that cannot be categorized are still recorded with separate entities. According to Table 4, the algorithm based on CNN has the highest number of journals with a percentage of 7.5%. Followed by genetic algorithms and morphological-based algorithms with a percentage of 3.8%. The rest there are 40 algorithms with a percentage below 2%. The algorithm that is often used to detect image errors is an algorithm based on CNN (convolutional neural networks). For example, Le Zhang et al (2019) used a CNN-based algorithm called the Fisher Discriminative 3D CNN Model. The 3D CNN model uses 3-dimensional blocks to perform detection, and fisher discriminative functions to support the discriminative criterion function of 3d CNN. However, the dataset used in their study is still relatively small. In the future, they plan to develop image detection not only for the left valve but also for other parts of the heart. Ichim and Popescu (2020) used Deep Convolutional Neural Networks and chose two types of CNN models, ResNet101 and AlexNet. ResNet is one of the best deep neural networks in the classification, while AlexNet is a CNN that uses color input in images and filters images to reduce training time.

Table 4. Algorithms Used to Detect Image Errors

Algorithms	Total	Journals No.	Percentage
CNN based algorithms	4	[P7],[P10],[P14],[P24]	7.5%
genetic Algorithms (GAs)	2	[P1],[P28]	3.8%
morphologically based algorithm	2	[P26],[P30]	3.8%
an algorithm based on Clifford's algebra	1	[P2]	1.9%
Error Level Analysis (ELA) algorithm	1	[P4]	1.9%
Color Filter Array (CFA)	1	[P4]	1.9%
Advanced Boundary Distinguishing Noise Detection Algorithm (ABDND)	1	[P5]	1.9%
depolarization weighted mean filtering algorithm	1	[P5]	1.9%

RQ3: the method used to detect image errors

The methods and frameworks used in each journal usually use a method called separate research. Because of that, the method used in each journal is categorized again based on the theoretical basis of the method. For methods that cannot be categorized, in the data with a separate entity. As displayed in Table 5, the most widely used methods are machine learning methods with a percentage of 27.27%, deep learning methods with a percentage of 20.4%, and artificial intelligence with a presentation of 6.82%. The machine learning-based method is the most widely used method for detecting image errors. Machine learning is a technique that is commonly used to detect image flaws since it requires training data. Machine learning may run automatically without any specific programming after being taught using training data. Adel Bakhshipour, for example, utilizes machine learning approaches to categorize plants to discriminate between pests and vegetable harvests. Ensemble learning is the branch of machine learning employed, in which learners are trained concurrently to answer the same issue. Lee et al (2019) employed a machine learning approach combined with morphological analysis to determine the worthiness of banknotes or banknotes by inspecting smudges on the surface of the banknotes.

Table 5. Methods Used to Detect Image Errors

Methods	Total	Journals No.	Percentage
machine learning	12	[P5],[P9],[P12],[P13],[P21],[P26],[P27],[P28],[P30],[P39],[P41],[P48]	27.27%
deep learning	9	[P1],[P7],[P8],[P18],[P24],[P29],[P33],[P38],[P45]	20.45%
artificial intelligence	3	[P14],[P36],[P47]	6.82%
Clifford Algebra	1	[P2]	2.27%
Demosaicing Algorithm	1	[P3]	2.27%
compressed sensing (CS)	1	[P6]	2.27%
multi-step anisotropic denoiser (MSAD)	1	[P10]	2.27%
weighted log-linear regression (WLLR)	1	[P10]	2.27%
Convolutional Sparse Coding	1	[P15]	2.27%
CSSPL Framework	1	[P16]	2.27%
spatiotemporal fusion	1	[P19]	2.27%
an asymmetric back-projection	1	[P20]	2.27%
bit planes slicing	1	[P22]	2.27%
Variance Local Image Fitting (VLIF)	1	[P23]	2.27%
Fourier transform-based techniques	1	[P25]	2.27%
motion compensated prediction (MCP)	1	[P32]	2.27%
geometric sensor model (EGSM)	1	[P35]	2.27%
encoder-decoder framework	1	[P39]	2.27%
Discriminative algorithms	1	[P40]	2.27%
general Residual Chaotic System (RCS)	1	[P42]	2.27%
Liu type estimator	1	[P43]	2.27%
Improved Self-Adjusting Model (iSEAM)	1	[P44]	2.27%
histogram equalization	1	[P50]	2.27%

RQ4: Measurement used to measure image error

Measurement is used to measure the accuracy of image error detection from the methods and algorithms used in the journal concerned. Most of the journals used in this study use more than one measurement. As shown in Table 6, the measurement methods that are often used are PSNR with a percentage of 9.89%, RMSE with a percentage of 8.89%, and MSE with a percentage of 6.67%. There are 45 other measurement methods with a percentage below 2%. PSNR is the most often utilized measurement for determining image error findings (Peak Signal to Noise Ratio). PSNR (Peak Signal to Noise Ratio) is the ratio of the highest signal intensity to noise that can impair image quality. PSNR is commonly expressed in decibels (db). Daehyon Jeong et al, for example, employ the PSNR measurement since it is the most generally used to assess the quality of images reconstructed from compressed data; typically, a good PSNR result has a value above 30 db, because, beyond that, the human eye cannot discern the difference.

Table 6. Measurements Used to Measure Image Error

Measurements	Total	Journals No.	Percentage
PSNR	9	[P2],[P5],[P8],[P9],[P20]' [P21],[P29],[P37],[P50]	9.89%
RMSE	8	[P8],[P12],[P15],[P19], [P35],[P43],[P44],[P48]	8.79%
MSE	6	[P2],[P3],[P5], [P24],[P28],[P33]	6.59%
SSIM	4	[P2],[P21],[P28],[P29]	4.40%
kappa coefficient	3	[P12],[P16],[P24]	3.30%
Entropy	2	[P2],[P6]	2.20%
f1 score	2	[P10],[P45]	2.20%
FP (True Negatives)	2	[P41],[P45]	2.20%
Jaccard index/similarity	2	[P23],[P38]	2.20%
TN (False Negatives)	2	[P41],[P45]	2.20%
type 2 error	2	[P10],[P45]	2.20%
type1 error	2	[P10],[P45]	2.20%
various	2	[P2],[P18]	2.20%

CONCLUSION

This systematic literature review discusses performing image error detection. By collecting 50 journals from 2019 to 2021. Types of images or data used to detect image errors mostly use images related to the medical image. The most widely used machine learning algorithm in the image detection process is an algorithm based on convolutional neural networks. The most frequently used method for detecting image errors is a method based on machine learning algorithms. The measurement most often applied to measure an image error detection method or algorithm is the Peak Signal to Noise Ratio. With the rapid development of current technology, technology for measuring image error detection will continue to grow. Finally, we hope that the results of this paper review on image error detection can be used to ensure image quality and integrity in various applications in future research.

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