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Article

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Journal of Open Innovation: Technology, Market, and Complexity

Systematic Review

Innovative Region Convolutional Neural Network Algorithm for Object Identification

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Abstract: Object identification is a part of the field of computer science, namely, image processing, whose research continues to innovate. Object identification describes an object based on the main characteristics of the object. Many research innovations related to object identification have been carried out to obtain optimal identification results. The convolutional neural network (CNN) is one of the algorithms that is widely used by researchers in the field of object identification or object recognition in digital images. The purpose of this study was to analyze the development of object identification in the search for the best algorithm in terms of the speed and efficiency of identification. The article data used were obtained from several sources, namely, Dimensions AI, Science Direct, and Google Scholar. The database search results obtained 1041 articles in the form of publications from 2010–2021. Through a systematic literature review based on the articles obtained, 32 articles were selected. The evaluation of the articles was carried out in the form of article data visualization, object identification algorithm development, and the research objects used. CNN's research innovation is growing rapidly, with improvements being made to the identification techniques in its algorithmic architecture. The use of the CNN algorithm in the identification of image objects, starting with the region CNN technique, is improved with Fast R-CNN, Faster-CNN, and Mask R-CNN. The object of research has developed from facial recognition and the identification of moving images to the introduction of ancient manuscripts that are useful for the development of history and tourism. The successful identification of ancient scripted texts will greatly assist the availability of such manuscripts in a digital format, which allows for further multidisciplinary research. The availability of ancient manuscripts in a digital format also helps the government to preserve culture and increase people's understanding of the culture they have.

Keywords: object identification; ancient manuscripts; R-CNN; Fast R-CNN; Faster R-CNN; Mask R-CNN

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1. Introduction

Image processing technology has become an important technology for machine learning and artificial intelligence (AI) tasks [1]. The continuous development and innovation of image processing technology helps AI algorithms to obtain relevant image information. To achieve machine visualization, object detection algorithms attempt to recognize all target items in the image and obtain category and object location information. The purpose of object detection is to identify and locate one or more entities that have meaning in still or moving images [2].

The rapid development of science and technology in the field of image processing in recent years has led to the potential to identify objects not limited to face recognition or certain objects. Further research has led to the ability to identify historical objects that are very important to the wider community. Object identification or recognition involves the automatic extraction and classification of an object [3], and the automation of the object identification process requires proper machine learning. One of the machine learning approaches that is often used for object recognition in images is the convolutional neural network (CNN) [4].

The identification process goes through several stages, namely, preprocessing, main process, and postprocessing. To produce an algorithm that can identify manuscripts well, it is necessary to find the right method for each stage of the process. The study of object identification is currently developing and attracting the attention of many researchers. The identification of objects in the image requires matching the characteristics of the objects in the image [5]. The CNN algorithm is widely used for object recognition as it can identify and recognize digital objects [6]. The obstacles in researching object identification are the detection of small objects among larger ones and against complex backgrounds. This poses a challenge to continue to develop the best innovations that obtain accurate results.

2. Materials and Methods

2.1. Scientific Article Data

In this study, literature focusing on object identification using CNN was identified and selected for review. The main focus was object identification using the region CNN algorithm on several different objects. In accordance with scientific developments, the region neural networks reviewed are Fast R-CNN, Faster R-CNN, and Mask R-CNN techniques.

The data used were articles obtained from several indexed sources, namely Dimensions AI, Science Direct, and Google Scholar. The articles were published from 2011 to 2021, so ten years of the database were used. The representation of the data was achieved using Vos Viewer from the searches performed using the Publish or Perish software by selecting the Google Scholar data source. In selecting the data using a PRISMA procedure, the data sources were taken from the selected database, the keywords entered were "object identification" and "ancient manuscripts" and "R-CNN" or "region convolutional neural network" or "fast R-CNN" or "faster R-CNN" or "mask R-CNN" with a maximum yield of 1041 articles as shown in Table 1 below.

Table 1. Four types of keywords.

Type	Keywords
I	Object Identification AND Ancient Manuscript AND R-CNN OR Region Convolutional Neural Network
II	Keyword I OR Fast R-CNN
III	Keyword II OR Faster R-CNN
IV	Keyword III OR Mask R-CNN

Table 2 presents the number of literature search results with the keywords shown in Table 1.

Table 2. Number of publications from three databases with four types of keywords.

Keyword	I	II	III	IV
Science Direct	24,739	21,163	942	943
Dimensions AI	185,986	170,753	1516	18
Google Scholar	34,500	23,500	2570	80

2.2. Selection of Literature

The literature data obtained from the Publish or Perish software were selected by deleting literature in the form of books or relating to topics that were considered irrelevant to the research. The selection was carried out to obtain literature related to the research objectives in the form of articles discussing object identification using the R-CNN algorithm with various research objects including ancient manuscripts. The obtained publications were checked one by one to ensure an appropriate range of results from journals, proceedings, and doctoral thesis were obtained, all of which were written in English as shown in Table 3. After making the selection, any duplicates obtained from the three databases were removed (filter 1). The selection continued by removing articles with titles that were less relevant to the identification of ancient manuscript objects (filter 2). The next stage of selection was to select articles with relevant abstracts (filter 3) and those with very relevant content to serve as references for the research to be carried out (filter 4).

Table 3. Results of the semi-automatic and manual selection.

Filter	**1**	**2**	**3**	**4**
Science Direct	242	143	21	3
Dimensions AI	18	12	8	9
Google Scholar	75	71	31	20
N	335	226	60	32

2.3. Methods and Systematic Data Analysis

This study carried out a systematic literature review of the published articles. The article data were assessed, identified, and interpreted based on the findings obtained after reading each article according to the object identification research topic using R-CNN. In the review process, a systematic evaluation of the literature is also needed so that there is no duplication or plagiarism with previous research.

In this study, the PRISMA procedure in Figure 1 used for the systematic analysis of article data was utilized according to the following stages:

(1) Visualization of article data related to the relationship between the article and the appropriate word topic.

(2) Mapping of the number of articles in each year (from 2011–2021) and providing general information. Intervention studies involving animals or humans, and other studies that require ethical approval, must list the authority that provided approval and the corresponding ethical approval code.

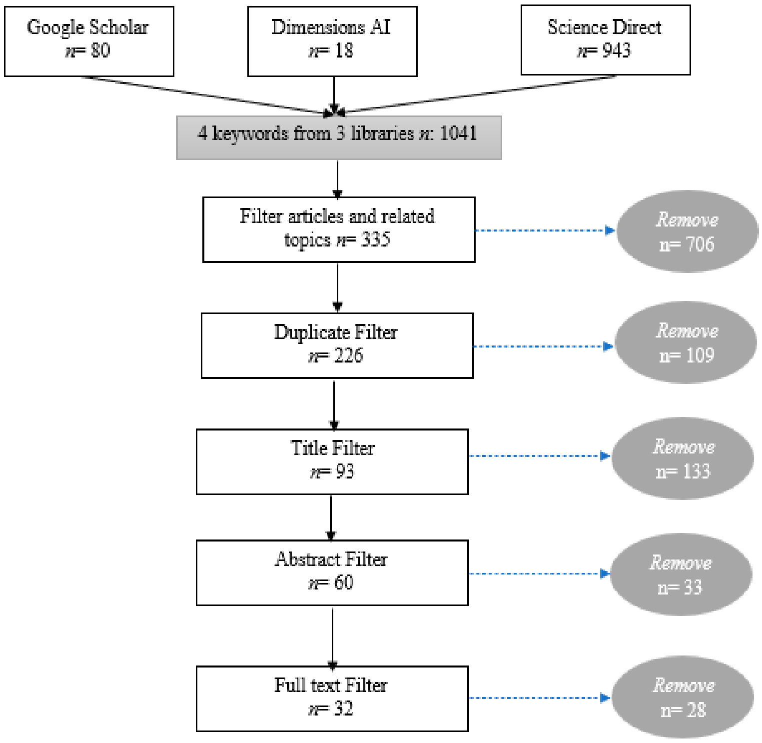

Figure 1. PRISMA systematic literature review procedure.

3. Results

The following section describes the results of the data analysis of 1041 articles. The explanation includes article data visualization, object identification research innovation, and research information using the R-CNN algorithm with different techniques.

3.1. Article Data Visualization

CNN research itself is closely related to the problems of object identification, image processing, object detection, classification, and network [7,8], as shown in Figure 2.

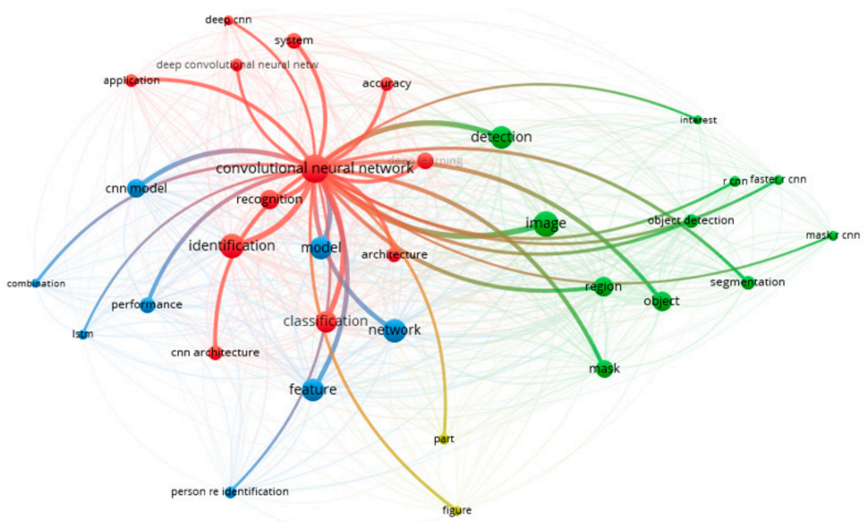

Figure 2. CNN's relationship with other fields of science.

CNN, as an algorithm architecture, is used as the basis for the development of R-CNN to obtain an optimal object identification algorithm. Research using Faster R-CNN and Mask R-CNN is still rarely carried out because it is still relatively new. The development of object identification studies using the latest R-CNN algorithm proposed by Girshik [9] is shown in Figure 3.

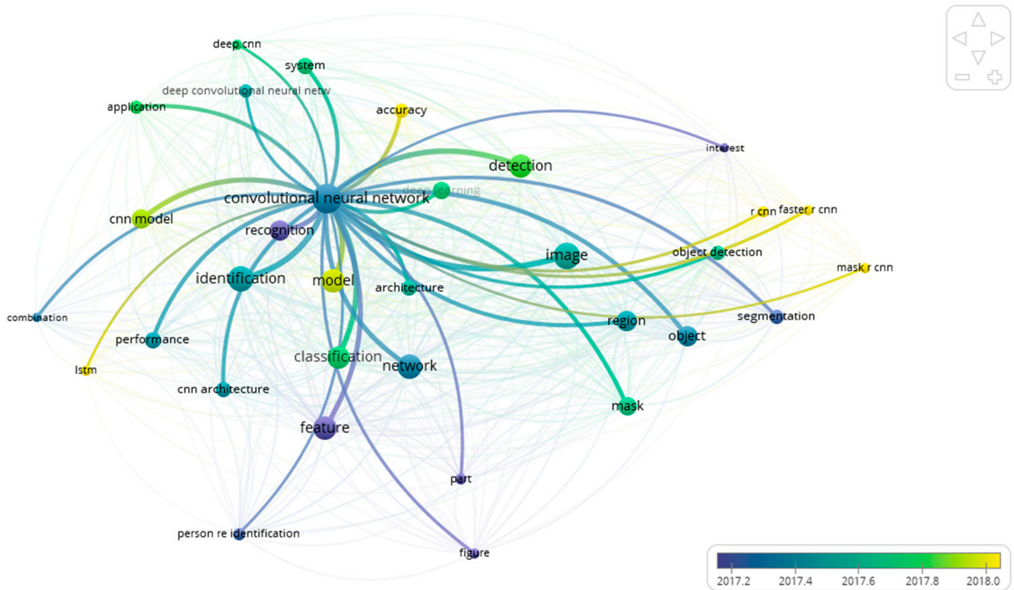

Figure 3. CNN algorithm innovation.

As the latest generation of R-CNN, Faster R-CNN and Mask R-CNN appeared around 2017–2018, and are marked in yellow in Figure 3 according to the color bar shown in the picture. Some papers use Mask R-CNN as an extension of Faster R-CNN, as it is a faster algorithm compared to other CNN algorithms [10].

3.2. Object Identification with R-CNN, Fast R-CNN, Faster R-CNN, and Mask R-CNN

CNN is one of the deep learning methods that currently has the most significant results in image recognition. This is because CNN imitates the image recognition system in the human visual cortex so that it can to process image information. However, CNN also has a weakness, namely, the need for model training, which takes a long time. Therefore, Girshick proposed R-CNN to shorten the processing time [11]. The research object identification model develops using the fastest search algorithm. A comparison of the speed of the test-time algorithm is presented in Figure 4 (source: https://towardsdatascience.com/ (accessed on 10 August 2022).

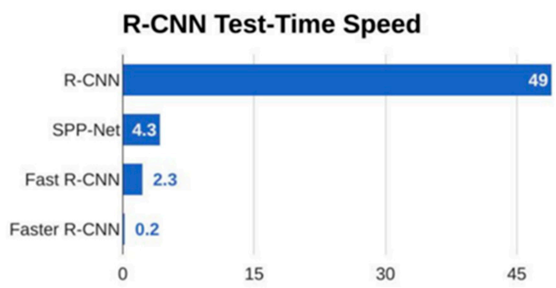

Figure 4. R-CNN test-time speed.

Thus, Fast R-CNN was developed as an improvement of the R-CNN algorithm, Faster R-CNN was developed as an improvement of the Fast R-CNN algorithm, and the latest Mask R-CNN model was developed from Faster R-CNN and its algorithmic model architecture.

Table 4 provides a summary of the four CNN models in the study in terms of the architecture of the algorithm model.

Table 4. Summary of the four CNN algorithm models.

CNN Model	Author	Approach Used	Objective	Result
R-CNN	[11,12]	• Labelling data regions • Feature point density (SIFT)	Region selection	Effectively speeds up the processing time
Fast R-CNN	[13]	• RoI pooling • Probability Softmax	Process acceleration	Faster than R-CNN
Faster R-CNN	[14]	Identifying regional proposals is done with a separate network (RPN)	Process acceleration	Faster than Fast R-CNN
Mask R-CNN	[10]	• Prediction of object masking for bounding box recognition • Developed from faster R-CNN • RoI align	• Facilitate training • Task generalization	Can perform other tasks in the same framework

The identification of image objects is an interesting topic in the field of computer vision. Object identification applications can be used in search engines, biometric security, attendance engines, or traffic security [15,16]. With the development of automatic machines and computers, the development of object identification algorithms such as R-CNN is also advancing rapidly. The R-CNN object classification approach uses a deep learning system to recognize objects. The proposed region becomes very important for the performance of R-CNN to identify individual objects accurately. Research is developing not only in terms of the speed of the algorithm, but also in terms of the object of research that is adapted to the desired application [17–19].

Object identification research has also begun to be used for applications in the field of culture, for example, to identify ancient objects both in two dimensions (manuscripts) and three dimensions (reliefs/statues) [20]. Ancient objects are very vulnerable and not very informative due to their age, so having digital data that can provide more information about these ancient objects will be very useful. Several researchers have found different methods to facilitate the reading and copying of damaged manuscripts [21,22]. The following Table 5. is a resume of the research related to ancient manuscripts.

Table 5. Summary of ancient manuscript research.

No	Author	Titles	Research Object
1	[23]	*Image Processing for Historical Newspaper Archives*	• Improve ancient image processing methods and degraded document images • Image processing method with character segmentation (Hough Transform)
2	[24]	*Combination of statistic and structural approach to scripts segmentation from line segmentation of Javanese manuscript image*	• Combines statistical and structural analysis to generate Java scripts from line segmentation of Java script drawings • Characters in the script are identified using the interconnect operation to identify the components of the script
3	[25]	*Appraisal of localized binarization methods on Tamil palm-leaf manuscripts*	Localized binary method for storing text information from digital Tamil manuscript images
4	[26]	*Evaluating Ancient Sundanese Glyph Recognition using Convolutional Neural Network*	CNN algorithm for pattern recognition of ancient Sundanese manuscript in lontar media
5	[5]	*Benchmarking of document image analysis tasks for palm leaf manuscripts from Southeast Asia*	Palm-leaf manuscript image analysis
6	[27]	*Thai Handwritten Recognition on Text Block-Based from Thai Archive Manuscripts*	Thai handwriting recognition using CNN
7	[28]	*Historical Arabic Manuscripts Text Recognition Using Convolutional Neural Network*	Arabic text recognition using CNN

4. Discussion

4.1. Development of Object Identification Research

The research on the identification of manuscript objects in the last ten years has grown quite significantly. Research results provided in the form of articles have increased based on the number of publications from 2011 to 2021, reaching 1041 articles after filtering redundancies from three databases. The identification of historical objects is more related to 3D objects [29], while research on identifying manuscript objects with non-Latin letters is still limited [30,31]. Several studies of ancient Sundanese manuscripts have been carried out [32,33], but the medium of this manuscript is palm leaves, therefore research on ancient Sundanese manuscripts using paper media is still lacking.

In image processing, the role of media objects is very influential in determining the right algorithm. Image processing goes through several stages, and if one stage uses another method, it can be said that the process uses a different algorithm.

4.2. CNN Algorithm Development for Object Identification

Articles published on the topic of object identification using CNN are generally related to deep learning [34,35], feature extraction [36], and classification [19]. After Girshick proposed a region-based convolution network for accurate object detection and segmentation [11], many researchers used R-CNN for more accurate object identification. Research using CNN develops the search for the fastest algorithm with high accuracy and precision, starting with the Fast R-CNN algorithm [13], Faster R-CNN [14], and Mask R-CNN [10].

The CNN algorithm is an algorithm that uses a convolution technique to obtain a sufficient amount of training data for object classification [37,38]. However, the amount of training data will affect the time-consuming training process and overfitting. Overfitting can occur due to too much training data, so the algorithm loses the ability to generalize [39]. R-CNN is proposed to reduce this overfitting problem [11]. The R-CNN algorithm uses the SVM classification technique, which is an additional module of the CNN algorithm circuit, thus increasing the processing time. Therefore, Fast R-CNN is utilized to correct deficiencies in R-CNN, namely, not using the SVM module, but using the Softmax probability as in CNN. Research continues on the search for the fastest algorithm, such as Faster R-CNN, which uses the region of interest (RoI) as the input for classification [14] so that it is ensured that only inputs with the considered characteristics will be classified. The next algorithm development is Mask R-CNN, which is based on the Faster R-CNN algorithm [10] and adds one input channel, namely, RoI Align, so that in addition to this algorithm's rapid detection capability, it is also possible to perform other tasks; for example, in addition to detecting faces, it can also detect poses on the screen in the same picture.

4.3. Convolutional Neural Network Algorithm and Open Innovation Engineering

In the development of science and technology, artificial intelligence has been used in various fields of life, and in-depth research on artificial intelligence has increased significantly. Research on the problem of target detection has achieved a high level of accuracy, but there are still many obstacles, especially for the detection of small targets against complex backgrounds that are often found in the fields of medicine, agriculture, or transportation [40,41]. This means that research in the field of target detection continues to increase, with various innovations being devised [42–44].

Research innovation using CNN utilizes the latest Faster R-CNN and Mask R-CNN algorithms, which have been tested and shown to have the best processing speed [45,46]. Research in the field of history and culture is very helpful for local governments to preserve cultural heritage and provide public knowledge of its cultural history. The CNN algorithm has been used in several studies with text objects [47], especially ancient text manuscripts in the fields of history and culture, which are prone to the loss of information, as shown in Table 2. The CNN algorithm is powerful enough to detect objects more quickly and accurately [48], although the challenge of detecting objects among larger ones and against more complex backgrounds [49,50] has led many researchers to use this algorithm as a basis for development and innovation to achieve better research results [51,52].

5. Conclusions

Identification applications are widely used in everyday life, such as in biometric detection for the benefit of employee attendance within a company or vehicle number plate detection for the benefit of road users' safety. Thus, object identification research is of particular importance for further applications in human life.

The development of various object identification algorithms with CNN architecture has been discussed in this article. The discussion began with region CNN, which implements a bounding box, and then Fast R-CNN, which has a better processing speed than R-CNN, and finally Faster R-CNN, with the best processing speed in identifying objects. Mask R-CNN was then introduced as an object identification algorithm that is more accurate and has the best processing speed because it was developed based on the Faster R-CNN algorithm. The topic of new algorithms as a development of the existing R-CNN algorithms is still open for further study.

The R-CNN algorithm can also be developed to assist the government in preserving culture and increase public understanding of historical heritage by developing an ancient manuscript object identification algorithm. There are very few papers concerning the object identification of ancient manuscripts using CNN compared to the number of ancient manuscripts in Indonesia. Therefore, the research of ancient manuscripts is a critical challenge, and is quite an interesting approach to use to create a more effective object identification algorithm.

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