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A Scoping Review of Classification of Concrete Cracks using Deep Convolution Learning Approach

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ABSTRACT

An important factor that causes defect in the concrete structure is the systematic damage and it is very difficult to detect the cracks by visual examination. Digital image processing has proven to be one of the best substitutes for the monitoring of the cracks. A traditional filter based on image processing algorithm is a classical approach for monitoring the cracks. Thereafter, the deep learning-based methods have been implemented to detect and classify the cracks on the concrete images and have shown significant results. The convolution neural network-based models have fairly observed and graded the cracks giving better performance in terms of accuracy, precision and recall. After the bibliometric review of the existing literature, comparison of the performance of different models and existing methods can be observed.

Keywords: *Concrete Crack, Image Processing, Bibliometric, Convolution Neural Network, Survey, Filter Techniques, Segmentation.*

1. Introduction

Concrete structures play an important role in the civil building and construction field. During the construction and further phases, the concrete is vulnerable to swift cracking which may eventually lead to the collapse of the buildings and structures. Various internal and external factors affect the toughness and bearing capability of the concrete structures which eventually leads to collapse of the buildings. The structures are also prone to vibrations due to penetration of moisture. All these factors add up to the increased repair costs and eventually lead to a national burden [1]. Through the use of advanced technologies, it is possible to provide solutions to these problems [2]. Financial losses and loss of life and casualties can be avoided by the means of early detection of the concrete cracks [3]. Accurate measurement of cracks is vital but time consuming due to human inspection. Hence, there is a need for higher processing speed which is possible by automated method of crack detection [4]. Thus, digital image processing is a viable option for tracking the cracks as the identification is possible on the basis of photographs which may be affected by factors like size, shades, blemishes, noise and illumination in the photographs [5]. Also, identification of region of interest and differentiating it from the insignificant background is essential in order to improve the performance of the model and eliminate the noise [6]. Often, useful information is present in the crack images that contains the gap. Usage of different types of filters like vector, mean and median is essential in order to increase the performance and accuracy of the model [7]. A vigilant inspection of the concrete structure is necessary and in order to achieve accurate diagnosis of the cracks, classification of the cracks is a critical factor [8]. Defects from images can be reliable tracked using machine learning models like random forests or decision trees [9, 10]. In spite of having a huge dataset, the performance of the machine learning algorithm has not proven to be upto the mark. Hence to overcome these drawbacks, there is a need to shift to the deep learning-based algorithms for identification of the cracks. Thus, ANNs and CNNs have been used extensively to solve the problems of crack identification [11,12]. The basic architecture for classification is shown in Fig. 1 where in image is given as input to the pre-processing block which contains filtering and noise removing stage. Thereafter, the data is given to the segmentation block which acts as a crack segmentator. The pre-processed images are sent to the segmentation block which focusses only on the cracks and separates the background. Then the output images are given to the classifier which predominantly uses convolution neural networks (CNN) model to extract the features and classify the cracks from the surfaces of the concrete structures. Thus, the basic classifier helps to find and classify the cracks.

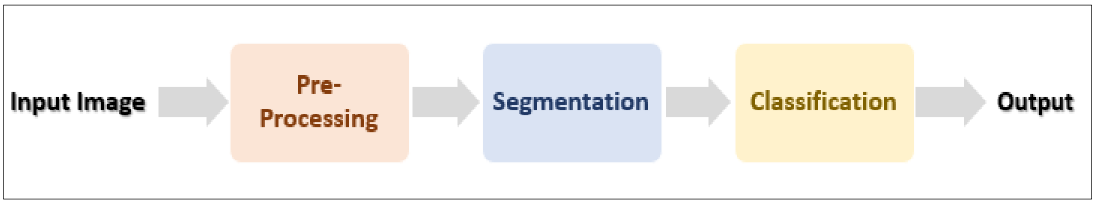


Fig. 1: Architecture of Classification Approach

As depicted in Fig. 2, the CNN model consists of feature extraction and fully connected layer. Feature extraction is done by convolution layer and pooling layer. Final layer is a interconnected layer. CNN is widely used in the cracks and defect detection algorithms due to its exceptional feature extraction capability. Images fed to the classifier may have different angles, weather conditions, intensity of the light for different cracks. Thus, defect recognition and detection play a very important in these kinds of applications. In the first phase of feature extraction, colour and texture-based characteristics are extracted. To improve the performance of the model, more layers can be added to the fully connected layer in the deep convolution network. The features extracted will be useful to enhance the performance of the classifier.

Convolution and max pooling layers are included in the characteristic extraction block and different parameters like dimension of the filer and steps of the sliding window may be adjusted as per requirement in order to boost the classifier accuracy in terms of efficiency and accurateness. Table 1 summarizes details about all papers referred in relation concrete crack detection techniques.

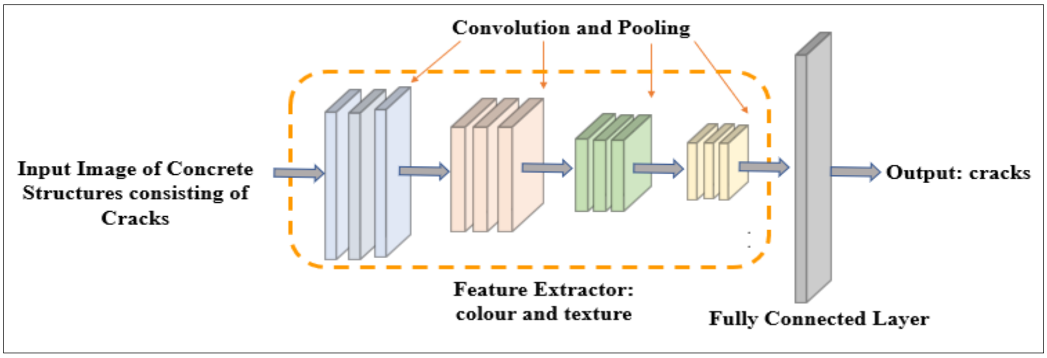


Fig. 2: Convolution Neural Network as Feature Extractor

Table 1: Summary of Concrete Crack Detection Work

Reference Number	Year	Keywords	Significance
1	2018	Failure to Act Report , Infrastructure Report Card	ASCE publishes a report which informs about the grade of the categories of the infrastructure. (A: F)
2	2018	crack; CNN; deep learning; Alex Net; aerial vehicle	Images and videos fetched from UAV and evaluated using CNN
3	2018	Crack detection; damage assessment; image processing; percolation model; digital; image correlation	use of Digital Image Correlation & mathematical tools like Wavelet transform (WT)
4	2018	crack detection, image processing ,deep learning algorithms	Image processing and deep learning-based crack detection methods based
5	2018	Feature extraction; Crack detection; image processing; filter segmentation	Detection of crack in engg structures using image processing tools
6	2017	road safety; maintenance; crack detection; pavement crack; automatic detection	Use of decision tree in order to detect and classify cracks
7	2018	Image restoration and processing; noise removal; impulse noise	survey on impulse noise removal technique , comparison of performance of all the techniques.
8	2017	Crack monitoring and detection; bridge assessment; image processing	Assess concrete bridge cracks using MCrack-TLS technique
9	2016	Deck inspection; adaboost; computer vision; pattern recognition and crack detection	spatially tuned robust multifeatured algorithm used
10	2018	crack detection; deep learning algorithms; cnn	CNN classifier to detect cracks and integrating it to a smart phone application
11	2016	concrete cracks, computer vision	Automatic Detection of concrete cracks using computer vision-based system

Reference Number	Year	Keywords	Significance
12	2017	concrete cracks , Canny and Sobel, edge detection, computer vision	Use of Canny and Sobel edge detection methods and related study
13	2018	solar cell, photoluminescence, micro-crack	novel method to classify micro-cracks in Photoluminescence (PL) images of polycrystalline solar cells is proposed.
14	2016	crack identification, extreme machine learning	ELM used to identify crack states in the beam
15	2017	Machine vision; unwashed eggrack; detection	Detection of cracks in eggs
16	2018	support vector machine; ppavement crack detection; probabilistic generative mode; probability	use of SVM to compute the probability maps
17	2019	crack detection , SVM, OTSU, segmentation	Use of SVM to classify pavement cracks and OTSU for segmentation.
18	2019	crack detection, CNN, feature extraction	crack detection on surfaces of concrete tunnel
19	2017	automatic, crack detection, segmentation	Method to detect cracks in photographs
20	2017	CNN; Pavement crack detection; Transfer learning	New method for crack detection
21	2018	image-adaptive thresholding, crack detection, structural ,cracks	Detect the cracks in the concrete structure using image-based method
22	2018	crack identification, deep learning, FCN	FCN used to measure different cracks at pixel level.
23	2018	Bilateral Filter; Speckle suppression; PSNR; SSIM; SSI	performance analysis of bilateral filter for SSI- PSNR-SSIM.
24	2017	Digital Noise, SMF, PSNR;MSE;IEF;VMF	Min MSE filtering technique to remove noise
25	2016	Segmentation; restoration; fuzzy c - mean	Application of image processing algorithms
26	2021	Segmentation; computer vision; concrete surfaces	CNN- ACM Integration
27	2020	OTSU; entropy segmentation; crack; concrete	Segmentation of digital image
28	2020	AI, CNN, Concrete Structures	2-dimensional CNN are used for crack image detection
29	2020	CNN; Computer vision ; Deep learning; Automated crack detection	Hierarchical deep learning network using a spatial channel is developed for crack detection.
30	2020	Detection; quantification; damage assessment; Image-processing	Graphical abstract about cracks
31	2020	Width assessment; temperature gradient; Thermal infrared radiances; Statistical analysis	Use of TIR camera properties for crack analysis
32	2020	Segmentation; stereo-vision, deep learning	Photogrammetric method is used for reconstruction of crack images
33	2020	CNN; crack detection; ensemble learning; transfer learning	DCNN ensemble approach aggregating results for individual models
34	2020	Crack-measurement ; SOP; monocular vision;	combo of monocular-vision & image-processing

Reference Number	Year	Keywords	Significance
35	2020	Crack detection; Deep learning- CNN; health monitoring	Concrete crack auto segmentation
36	2020	Non-destructive testing; Deep learning- CNN	CNN model for positive and negative crack images
37	2020	Crack-measurement; DIP; Smartphone-App	Non contactable measurement of concrete cracks using an app
38	2020	CNN, Crack Detection, Transfer Learning	Comparison based on MobileNetV2, DenseNet201, and InceptionV3 models for crack structures
39	2020	Fully-CNN; pavement crack	CNN based on ResNet-101 is used for identification of pavement cracks.
40	2019	image identification; minimum-width-extraction; image- mosaic	mosaic algorithm is modified to realize image for effective splicing of crack images
41	2019	Structural-health-monitoring; image processing; visual-geometry-group network; semantic-segmentation	DCNN based autonomous detection of cracks method
42	2019	concrete crack, crack width, deep learning, image processing, mask rcnn	Mask and region based CNN is used
43	2018	CNN; DIP; ML;speeded-up-features	ML based approach for identification of cracks
44	2018	Concrete crack, image processing, drone	Device using the image processing for crack detection
45	2019	Crack detection Image processing Python OpenCV	OpenCV library for crack detection is used
46	2019	UAV Concrete Surface, Crack Detection	transfer learning approach for a pre-trained network to identify cracks
47	2018	Digital-sampling-moiré optical-crack growth- sensor; 2D crack growth, calibration,	Digital-sampling moiré system developed for 2D crack growth monitoring.
48	2018	Transportation systems-engineering Structural inspections; Bridge inspections	DIP based algorithm to detect concrete cracks.
49	2018	Edge-detection; OTSU-thresholding; UAVs; image-stitching, texture-analysis,	Crack detection techniques used -SURF &SIFT.
50	2018	UAV; Image-recognition, crack-width	Use of UAV to capture images of building surface cracks
51	2018	Multi-layer top-coat systems; poro-elastic road-surface; noise-reducing coating	multi-layered wearing course system development
52	2018	Width-measurement; B-spline level; phase-congruency	Crack-width measurement system based on Savitzky Golay filter
53	2013	Bridges, Gray-scale, Iterative methods, Image segmentation, Image edge detection, Concrete, Adaptive filters	Crack extraction using gray-threshold and canny iteration technique
54	2018	SVM; CNN	SVM & CNN for crack detection
55	2018	Vision based, crack detection, concrete features	Cascade feature based face detection method to find the cracks on concrete surfaces.

2. Preliminary Data Collection

This article is articulated by sending a query to the SCOPUS database using main keywords - as shown in Table 2.

Table 2 List of Keywords: Primary and Secondary

Primary Keywords	"Concrete Crack"
Secondary Keywords	"Image Processing" OR "Filter Techniques" OR "Convolution Neural Networks"

Source: http://www.scopus.com (accessed on 12th January 2021)

The basis for the research is the Scopus database using the keywords mentioned above as query strings. By using these keywords, 83 documents were retrieved out of which 69 were in English ,9 in Chinese, 4 in Japanese and 1 in German language as shown below in the Table 3.

Table 3 Trend for the Publishing Language

Language of Publication	Total Count
English	69
Chinese	9
Japanese	4
German	1

Source: http://www.scopus.com (accessed on 12th January 2021)

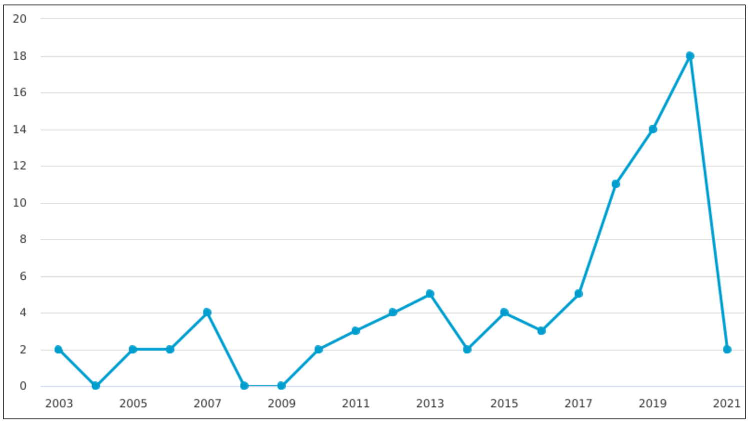
3. Bibliometric Information and Performance Analysis

After posting a query using the mentioned keywords on the Scopus database, the necessary information is retrieved in *.csv* format and expressed in terms of the following for the further analysis -

1) The information of the documents by – prominent authors, funding sponsors, source, year, type, contributing country, subject area and key affiliations is used for statistical analysis of the data.
2) Data representation is undertaken in the form of network diagrams and graphs which is based on the co-authorship, citation analysis, co-occurrence and bibliographic coupling.

4. Results and Discussion

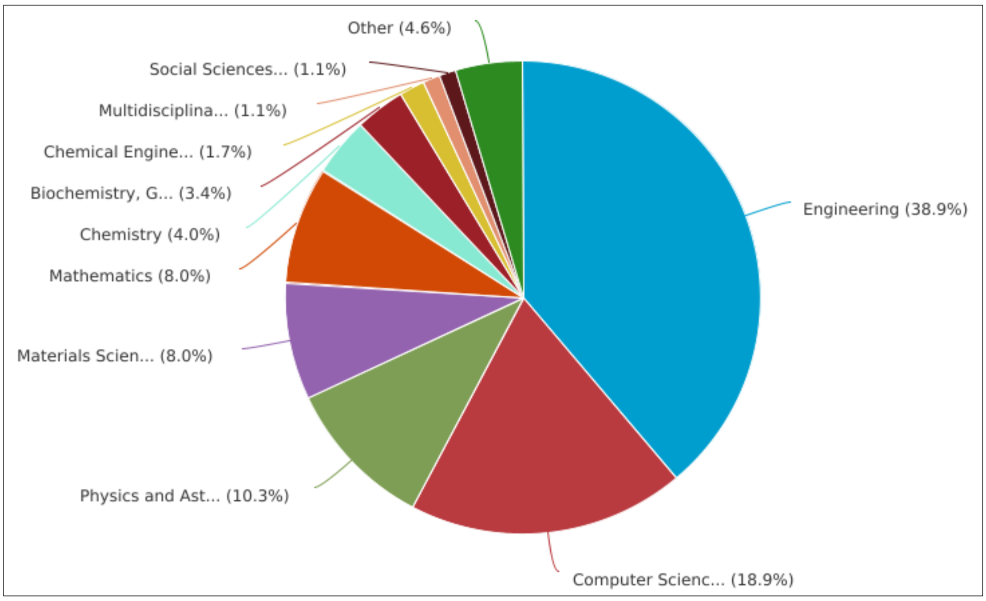
4.1 Preliminary Data Analysis



Year	Documents	Year	Documents
2021	2	2013	5
2020	18	2012	4
2019	14	2011	3
2018	11	2010	2
2017	5	2007	4
2016	3	2006	2
2015	4	2005	2
2014	2	2003	2

Fig. 3 Documents by Year
Source: http://www.scopus.com (accessed on 12th January 2021)

Fig. 3 shows documents by year. Years 2018 to 2020 are the active years or years wherein more number of publications were published. From 2003 to 2017, only a few publications were there. Fig. 4 shows engineering followed by computer science then physics and material science are the prominent subject areas. The same is evident from publications published in these areas.

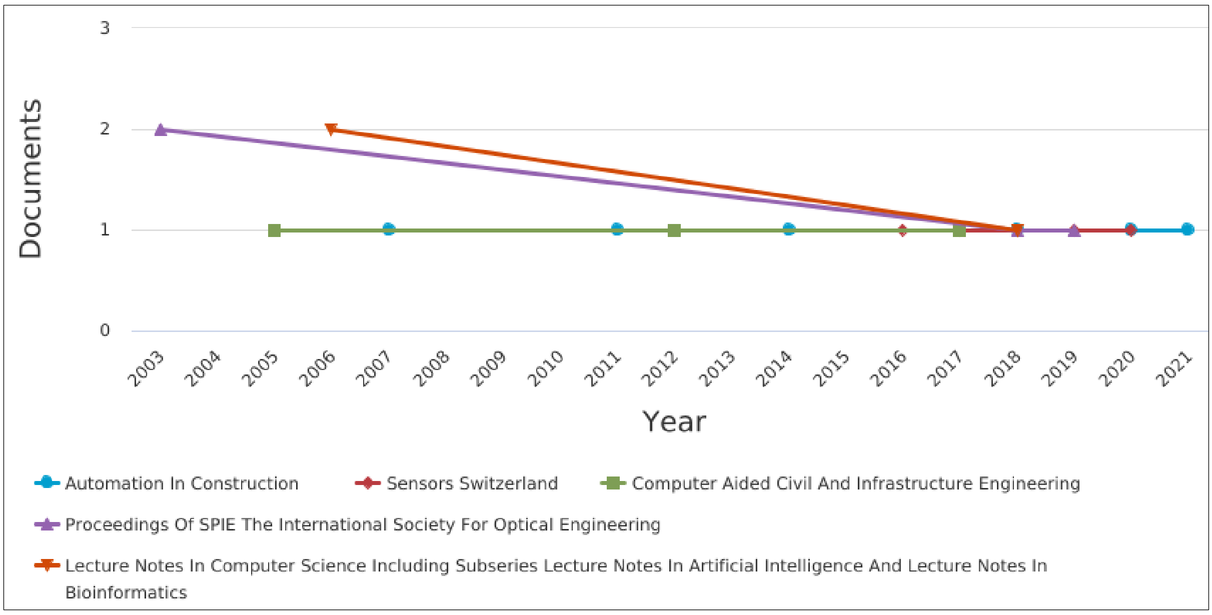


Subject Area	Documents
Engineering	68
Computer Science	33
Physics and Astronomy	18
Materials Science	14
Mathematics	14
Chemistry	7
Biochemistry, Genetics and Molecular Biology	6
Chemical Engineering	3
Multidisciplinary	2
Social Sciences	2

Fig. 4 Documents by Subject Area

Source: http://www.scopus.com (accessed on 12th January 2021)

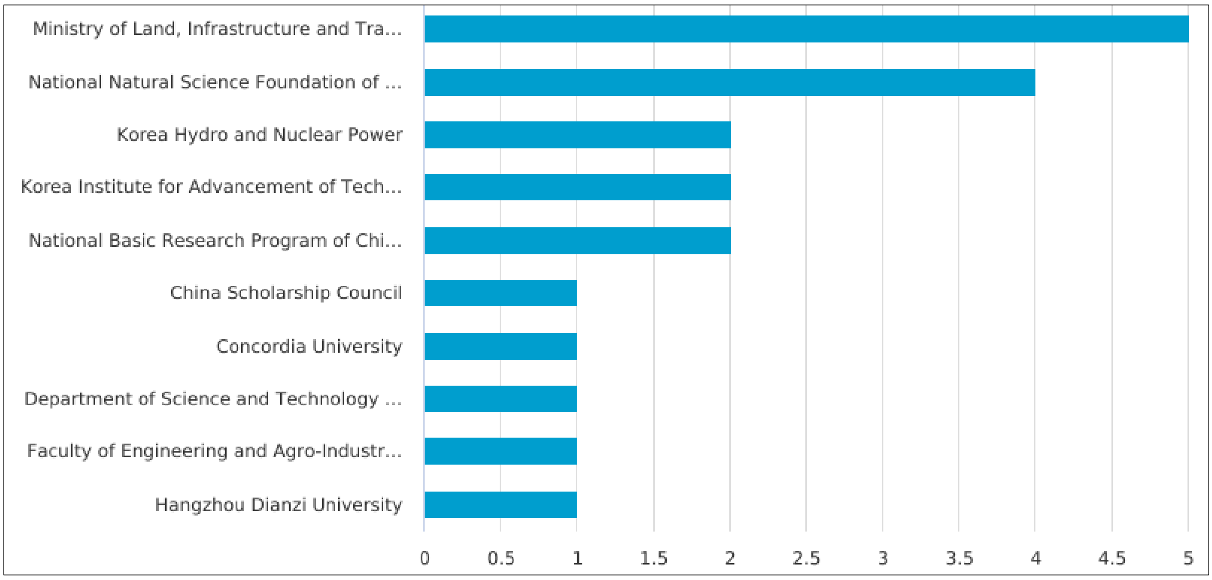
Fig. 5 shows main source titles related to the considered research area for bibliometric analysis. Automation in Construction, Sensors Switzerland and Proceedings of SPIE are the key source titles. It is also necessary to consider prominent funding sponsors related to the undertaken bibliometric research. Based on the publication count, Ministry of Land, Infrastructure and Transport, National Natural Science Foundation of China, Korea Hydro and Nuclear Power are the major funding sponsors. Fig. 7 indicates leading countries. China, South Korea and United States are top countries involved in the considered research topic. Fig. 8 and 9 are related to the prominent authors and key affiliations. Cho, S., Kim, H., Sim, S. H., are the main authors and Ulsan National Institute of Science and Technology, Silla University, Dalian University of Technology are the main universities. There are more number of journal articles, then conference papers, book chapters are review papers are very less. That's why this review cum bibliometric paper.



Source Title	Documents
Automation in Construction	7
Sensors Switzerland	5
Proceedings of SPIE The International Society for Optical Engineering	4
Computer Aided Civil and Infrastructure Engineering	3
Applied Sciences Switzerland	2
Cement and Concrete Composites	2
Information Japan	2
Zairyo Journal of The Society of Materials Science Japan	2

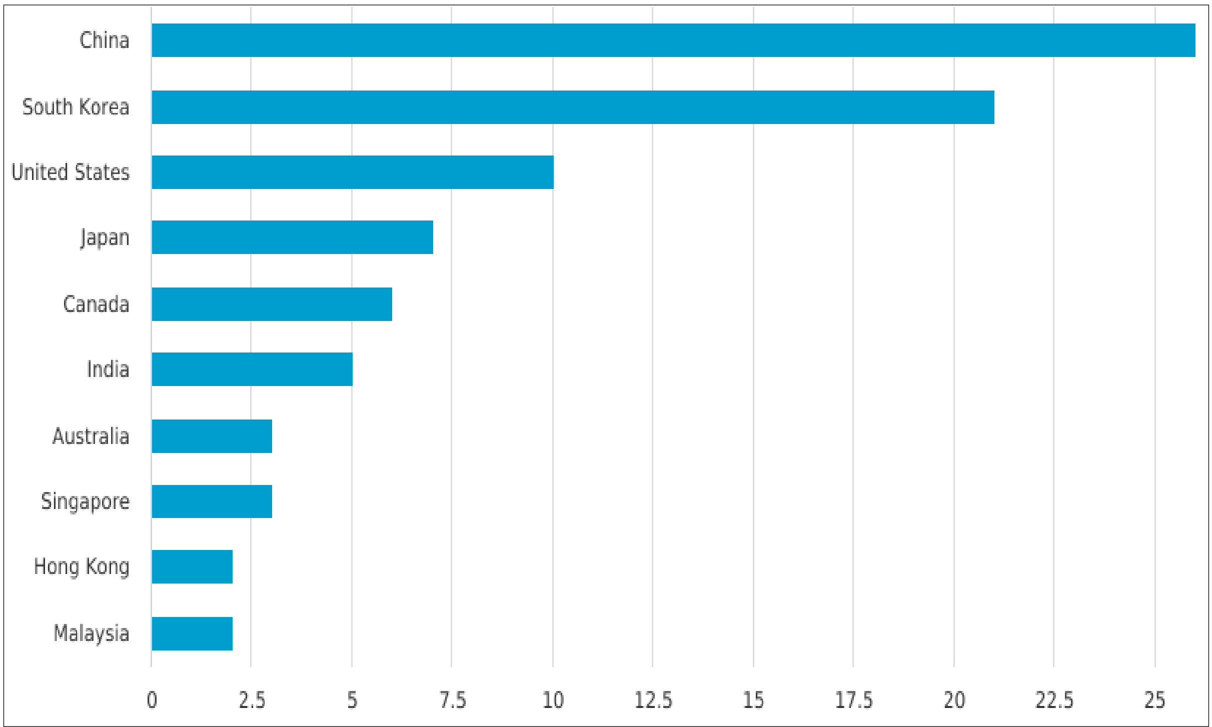
Fig. 5 Documents per year by Source

Source: http://www.scopus.com (accessed on 12th January 2021)



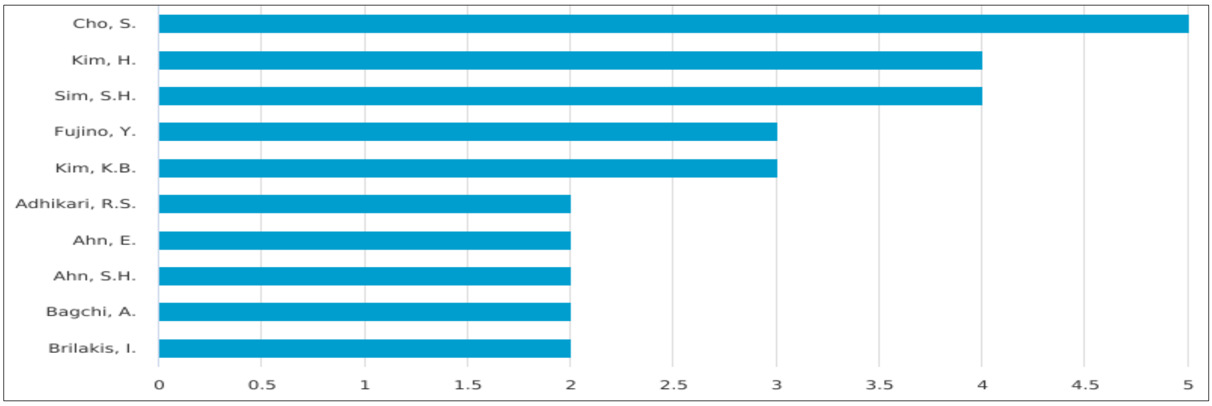
Funding Sponsors	Documents
Ministry of Land, Infrastructure and Transport	5
National Natural Science Foundation of China	4
Korea Hydro and Nuclear Power	2
Korea Institute for Advancement of Technology	2
National Basic Research Program of China (973 Program)	2

Fig. 6: Documents by Funding Sponsor
Source: http://www.scopus.com (accessed on 12th January 2021)



Country	Documents
China	26
South Korea	21
United States	10
Japan	7
Canada	6
India	5
Australia	3
Singapore	3
Hong Kong	2
Malaysia	2

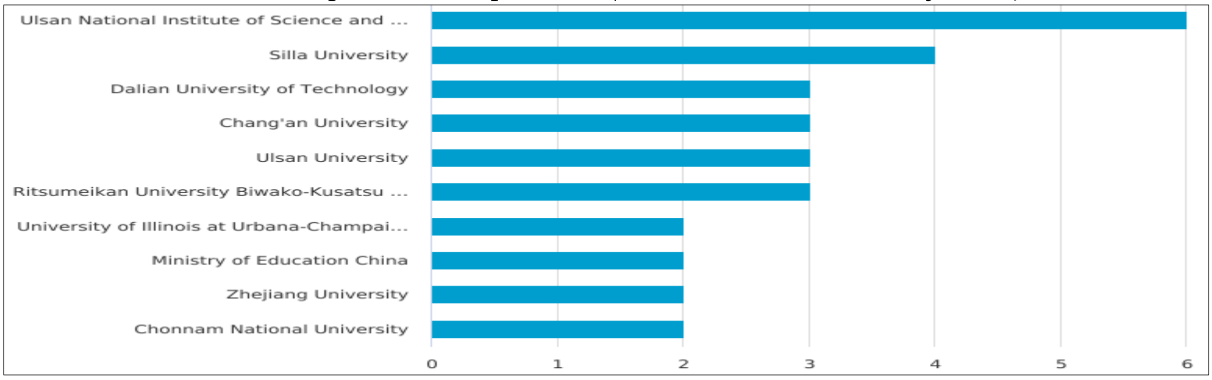
Fig. 7 Documents by Country or Territory
Source: http://www.scopus.com (accessed on 12th January 2021)



Author Name	Documents	Author Name	Documents
Cho, S.	5	Moselhi, O.	2
Kim, H.	4	Nishikawa, T.	2
Sim, S.H.	4	Nomura, Y.	2
Fujino, Y.	3	Peng, T.	2
Kim, K.B.	3	Peng, X.	2
Adhikari, R.S.	2	Shen, M.	2
Ahn, E.	2	Shigemura, K.	2
Ahn, S.H.	2	Shin, M.	2
Bagchi, A.	2	Spencer, B.F.	2
Brilakis, I.	2	Sugiyama, T.	2
Cha, Y.J.	2	Yang, S.	2
Jang, Y.M.	2	Yeoh, J.K.W.	2
Kavya, T.S.	2	Yoshida, J.	2
Kim, B.W.	2	Zhong, X.	2
Liu, Y.	2	Zhu, Z.	2

Fig. 8 Documents by Author

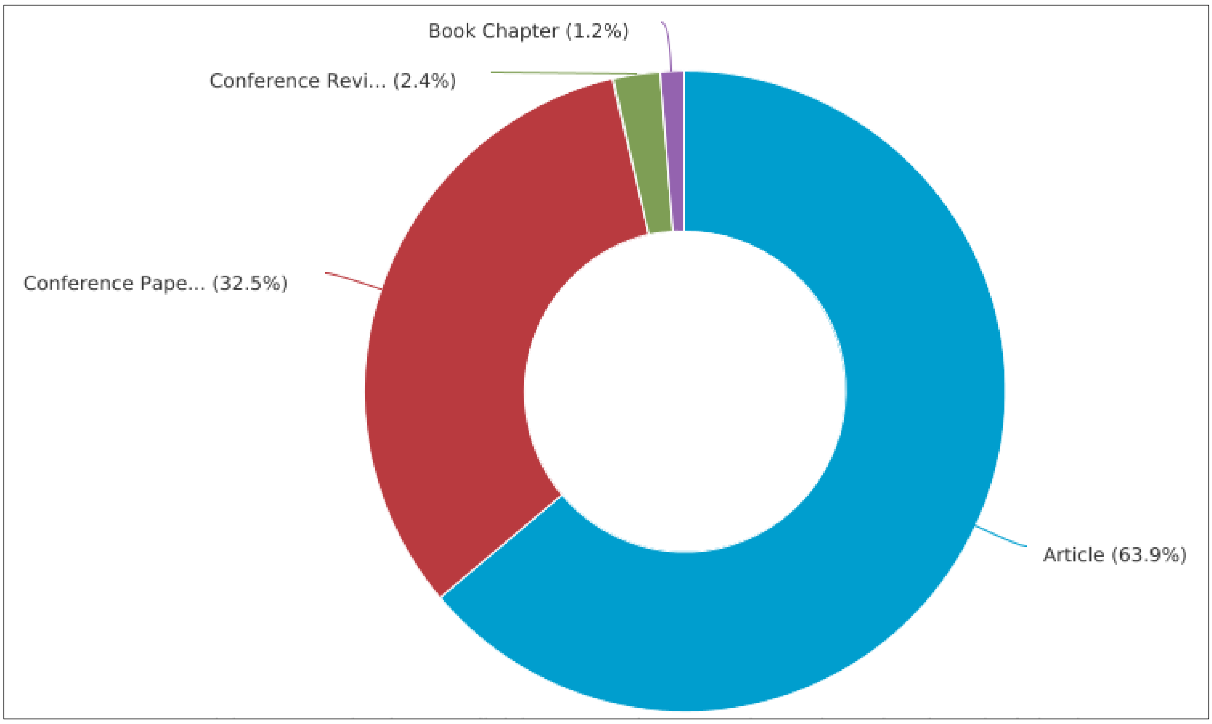
Source: http://www.scopus.com (accessed on 12th January 2021)



Affiliation	Documents
Ulsan National Institute of Science and Technology	6
Silla University	4
Dalian University of Technology	3
Chang'an University	3
Ulsan University	3
Ritsumeikan University Biwako-Kusatsu Campus	3
University of Illinois at Urbana-Champaign	2
Ministry of Education China	2
Zhejiang University	2
Chonnam National University	2
University of Manitoba	2
Yonsei University	2
National University of Singapore	2
Dong Eui University	2
Georgia Institute of Technology	2
Hunan University of Science and Technology	2
Hanyang University	2
The University of Tokyo	2
Tsinghua University	2
University of Seoul	2
Concordia University	2
DaLian Fisheries University	2
TongMyong University	2

Fig. 9 Documents by Affiliation

Source: http://www.scopus.com (accessed on 12th January 2021)



Document Type	Document
Article	53
Conference Paper	27
Conference Review	2
Book Chapter	1

Fig. 10 Documents by Type

Source: http://www.scopus.com (accessed on 12th January 2021)

4.2 Bibliometric Analysis through Networked Diagrams

This section is also important as it is very important to gain an insight about considered research area in the terms of relevant network diagrams. These diagrams give information about coappearance among keywords and authors, authors and source titles, linkage among papers through DOI, scape of involved references, co-citations of authors, involved institutes etc. Table 4 shows top cited articles.

Fig. 11 to 14 are interrelated as they show triangulation of information like main authors, keywords and journals. These details are reflected in fig. 12 to 14 respectively. Fig. 15 to 21 are related to the network diagrams. Authors and authors keywords are important as networked diagram for them (fig. 15) shows co-appearance among them which will in a way shows most frequently used keywords by them. Splitting testing, neural networks, concrete crack/s, image processing are the keywords used by the authors wang c., fujino y. etc. One more interesting fact about network diagrams is that fig. 16 shows details about author, author keywords, affiliations, and source titles.

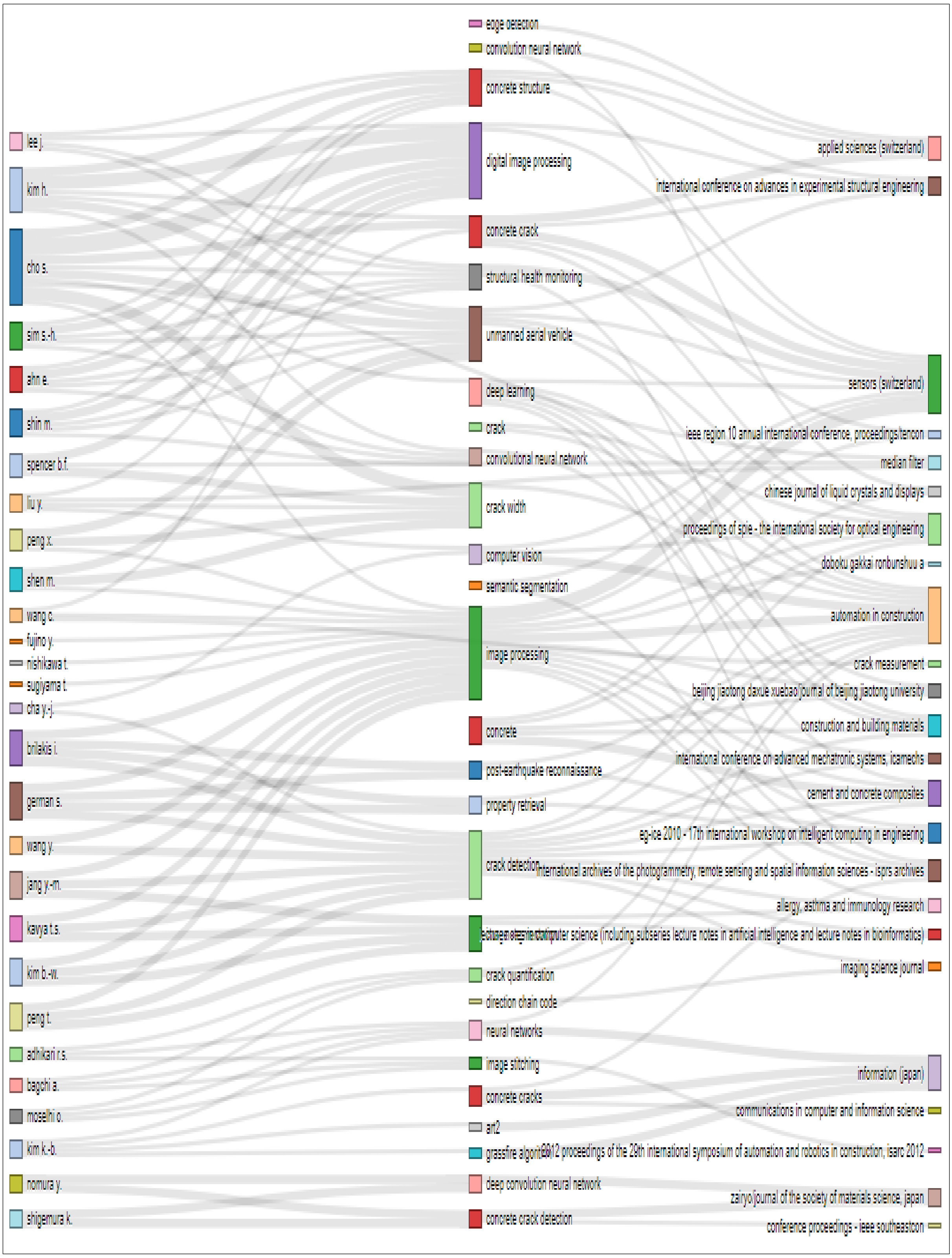


Fig. 11: Sankey Diagram: Authors-Keywords-Journal

Source: http://www.scopus.com (accessed on 12th January 2021)

Main authors

- cho s. (5 papers)
- kim h. (4 papers)
- fujino y. (3 papers)
- kim k.-b. (3 papers)
- liu y. (3 papers)
- sim s.-h. (3 papers)
- [no author name available] (2 papers)
- adhikari r.s. (2 papers)
- ahn e. (2 papers)
- ahn s.-h. (2 papers)
- bagchi a. (2 papers)
- brilakis i. (2 papers)
- cha y.-j. (2 papers)
- german s. (2 papers)
- jang y.-m. (2 papers)
- kavya t.s. (2 papers)
- kim b.-w. (2 papers)
- lee j. (2 papers)
- moselhi o. (2 papers)
- nishikawa t. (2 papers)
- nomura y. (2 papers)
- peng t. (2 papers)
- peng x. (2 papers)
- shen m. (2 papers)
- shigemura k. (2 papers)
- shin m. (2 papers)
- spencer b.f. (2 papers)
- sugiyama t. (2 papers)
- wang c. (2 papers)
- wang y. (2 papers)

Main keywords

- image processing (24 papers)
- crack detection (18 papers)
- concrete crack (13 papers)
- deep learning (8 papers)
- concrete cracks (7 papers)
- digital image processing (7 papers)
- concrete (6 papers)
- computer vision (5 papers)
- concrete crack detection (5 papers)
- crack width (5 papers)
- unmanned aerial vehicle (5 papers)
- concrete structure (4 papers)
- convolutional neural network (3 papers)
- crack (3 papers)
- edge detection (3 papers)
- image segmentation (3 papers)
- neural networks (3 papers)
- structural health monitoring (3 papers)
- art2 (2 papers)
- convolution neural network (2 papers)
- crack measurement (2 papers)
- crack quantification (2 papers)
- deep convolution neural network (2 papers)
- direction chain code (2 papers)
- grassfire algorithm (2 papers)
- image stitching (2 papers)
- median filter (2 papers)
- post-earthquake reconnaissance (2 papers)
- property retrieval (2 papers)
- semantic segmentation (2 papers)

Main journals

- automation in construction (7 papers)
- sensors (switzerland) (5 papers)
- proceedings of spie - the international society for optical engineering (4 papers)
- computer-aided civil and infrastructure engineering (3 papers)
- lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics) (3 papers)
- 9th international conference on structural health monitoring of intelligent infrastructure: transferring research into practice, shmii 2019 - conference proceedings (2 papers)
- applied sciences (switzerland) (2 papers)
- cement and concrete composites (2 papers)
- information (japan) (2 papers)
- international archives of the photogrammetry, remote sensing and spatial information sciences - isprs archives (2 papers)
- zairyo/journal of the society of materials science, japan (2 papers)
- 2012 proceedings of the 29th international symposium of automation and robotics in construction, isarc 2012 (1 papers)
- allergy, asthma and immunology research (1 papers)
- applied mechanics and materials (1 papers)
- bautechnik (1 papers)
- beijing jiaotong daxue xuebao/journal of beijing jiaotong university (1 papers)
- chinese journal of liquid crystals and displays (1 papers)

Fig. 12: Sankey Diagram: Authors-Keywords-Journal

Source: http://www.scopus.com (accessed on 12th January 2021)

2003

- proceedings of spie - the international society for optical engineering 1 paper

2004

2005

- proceedings of spie - the international society for optical engineering 1 paper
- computer-aided civil and infrastructure engineering 1 paper

2006

- lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics) 1 paper
- wuhan ligong daxue xuebao/journal of wuhan university of technology 1 paper

2007

- automation in construction 1 paper
- lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics) 1 paper
- bautechnik 1 paper
- ieej transactions on electronics, information and systems 1 paper

2008

2009

2010

- doboku gakkai ronbunshuu a 1 paper
- large structures and infrastructures for environmentally constrained and urbanised areas 1 paper

2011

- automation in construction 1 paper
- cement and concrete composites 1 paper
- communications in computer and information science 1 paper

2012

- computer-aided civil and infrastructure engineering 1 paper
- 2012 proceedings of the 29th international symposium of automation and robotics in construction, isarc 2012 1 paper
- jisuan lixue xuebao/chinese journal of computational mechanics 1 paper
- proceedings of the 28th international symposium on automation and robotics in construction, isarc 2011 1 paper

2013

- information (japan) 2 papers
- long span bridges and roofs - development, design and implementation 1 paper
- structure and infrastructure engineering 1 paper
- yi qi yi biao xue bao/chinese journal of scientific instrument 1 paper

2014

- applied mechanics and materials 1 paper
- smart structures and systems 1 paper

2015

- automation in construction 1 paper
- international conference on advanced mechatronic systems, icamechs 1 paper
- international conference on advances in experimental structural engineering 1 paper
- open civil engineering journal 1 paper

2016

- imaging science journal 1 paper
- journal of computing in civil engineering 1 paper
- matec web of conferences 1 paper

2017

- sensors (switzerland) 2 papers
- automation in construction 1 paper
- computer-aided civil and infrastructure engineering 1 paper
- mechanics of structures and materials: advancements and challenges - proceedings of the 24th australasian conference on the mechanics of structures and materials, acmsm24 2016 1 paper

2018

- automation in construction 1 paper
- sensors (switzerland) 1 paper
- proceedings of spie - the international society for optical engineering 1 paper
- lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics) 1 paper
- international archives of the photogrammetry, remote sensing and spatial information sciences - isprs archives 1 paper
- conference proceedings - ieee southeastcon 1 paper
- international journal of pavement engineering 1 paper
- procedia computer science 1 paper
- proceedings of the 3rd international conference on communication and electronics systems, icces 2018 1 paper
- science and technology asia 1 paper

2019

- 9th international conference on structural health monitoring of intelligent infrastructure: transferring research into practice, shmii 2019 - conference proceedings 2 papers
- sensors (switzerland) 1 paper
- proceedings of spie - the international society for optical engineering 1 paper
- zairyo/journal of the society of materials science, japan 1 paper
- eg-ice 2010 - 17th international workshop on intelligent computing in engineering 1 paper
- fuhe cailiao xuebao/acta materiae compositae sinica 1 paper
- ieee region 10 annual international conference, proceedings/tencon 1 paper
- international journal of mechanical engineering and technology 1 paper
- lecture notes in computational vision and biomechanics 1 paper
- shanghai jiaotong daxue xuebao/journal of shanghai jiaotong university 1 paper

2020

- automation in construction 1 paper
- sensors (switzerland) 1 paper
- applied sciences (switzerland) 1 paper
- cement and concrete composites 1 paper
- international archives of the photogrammetry, remote sensing and spatial information sciences - isprs archives 1 paper
- zairyo/journal of the society of materials science, japan 1 paper
- allergy, asthma and immunology research 1 paper
- beijing jiaotong daxue xuebao/journal of beijing jiaotong university 1 paper
- chinese journal of liquid crystals and displays 1 paper
- cmes - computer modeling in engineering and sciences 1 paper

2021

- applied sciences (switzerland) 1 paper
- sdhm structural durability and health monitoring 1 paper

Fig. 13: Top Journals

Source: http://www.scopus.com (accessed on 12th January 2021)

Fig. 14: Top Keywords from 2014 to 2021

Source: http://www.scopus.com (accessed on 12th January 2021)

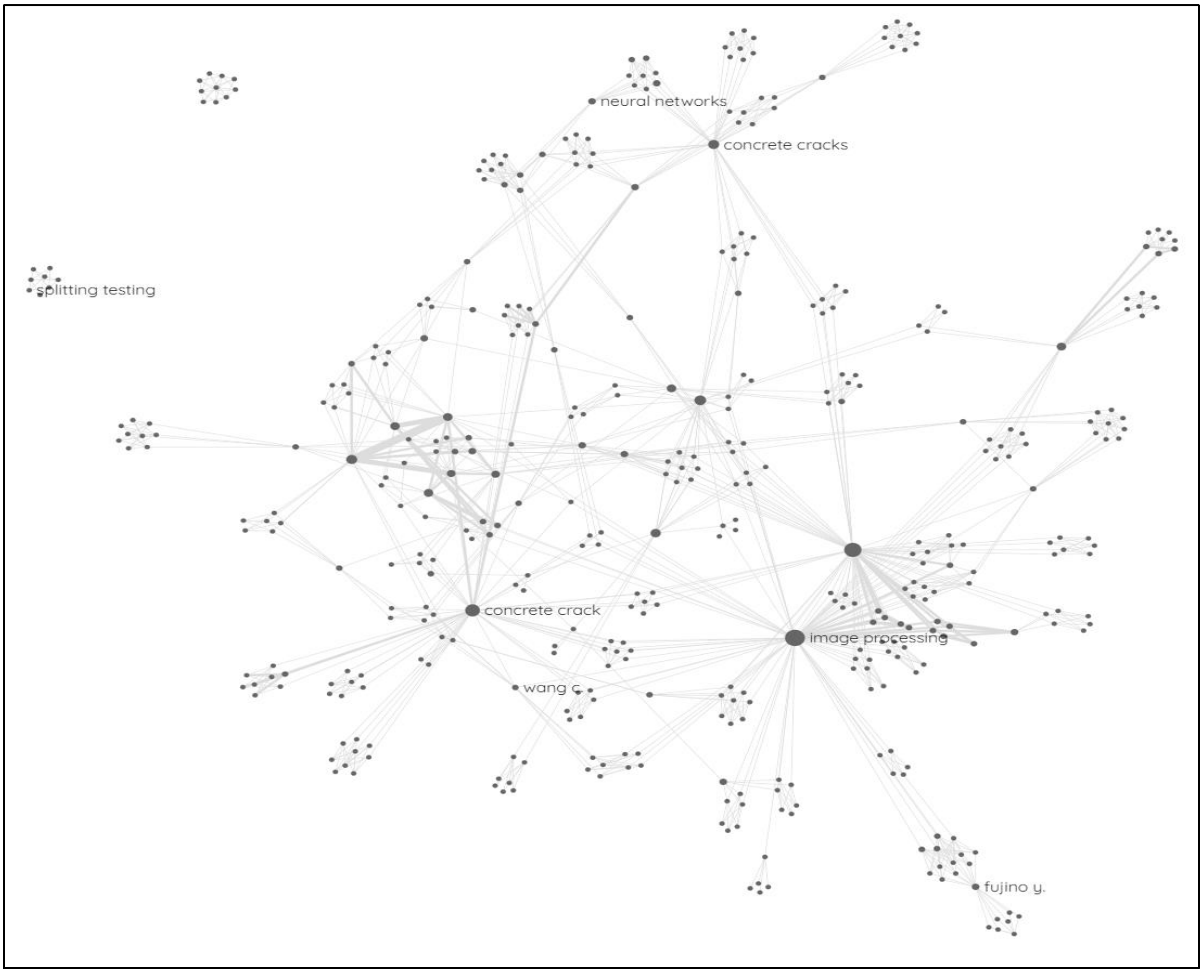


Fig. 15 Authors and Author Keywords co-appearing in the same papers
Source: http://www.scopus.com (accessed on 12th January 2021)

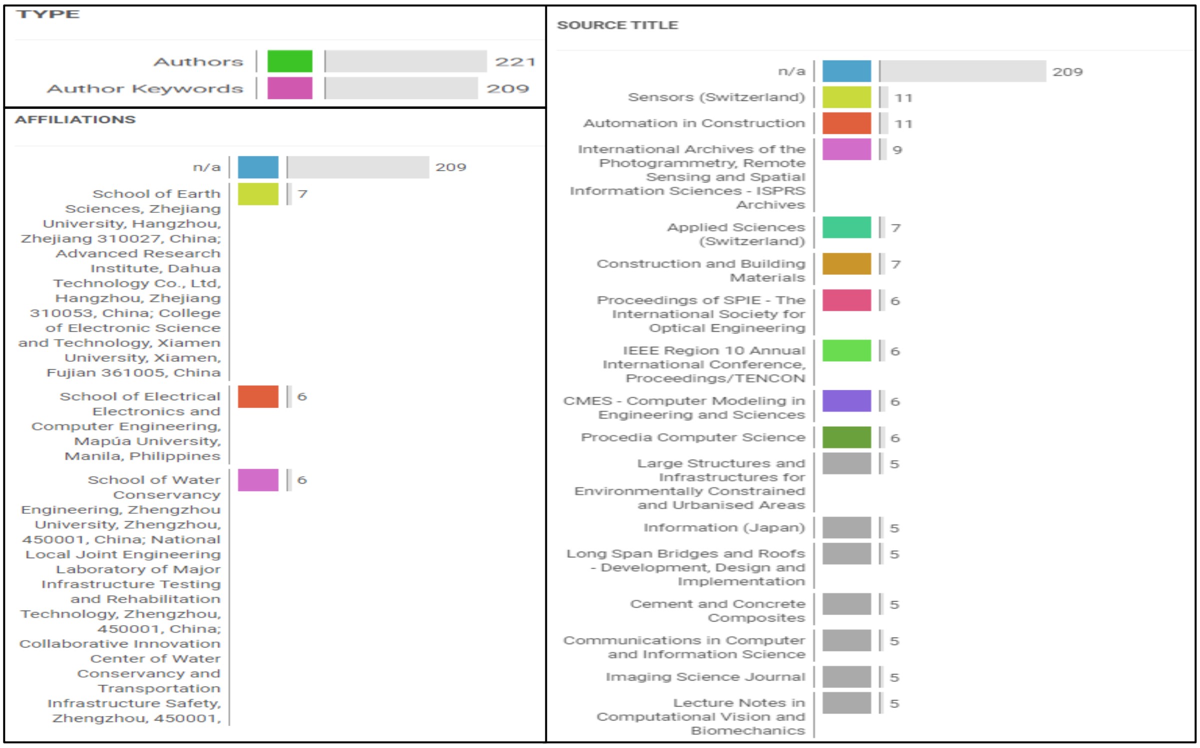


Fig. 16 Type, Affiliation and Source Titles for Network Diagrams

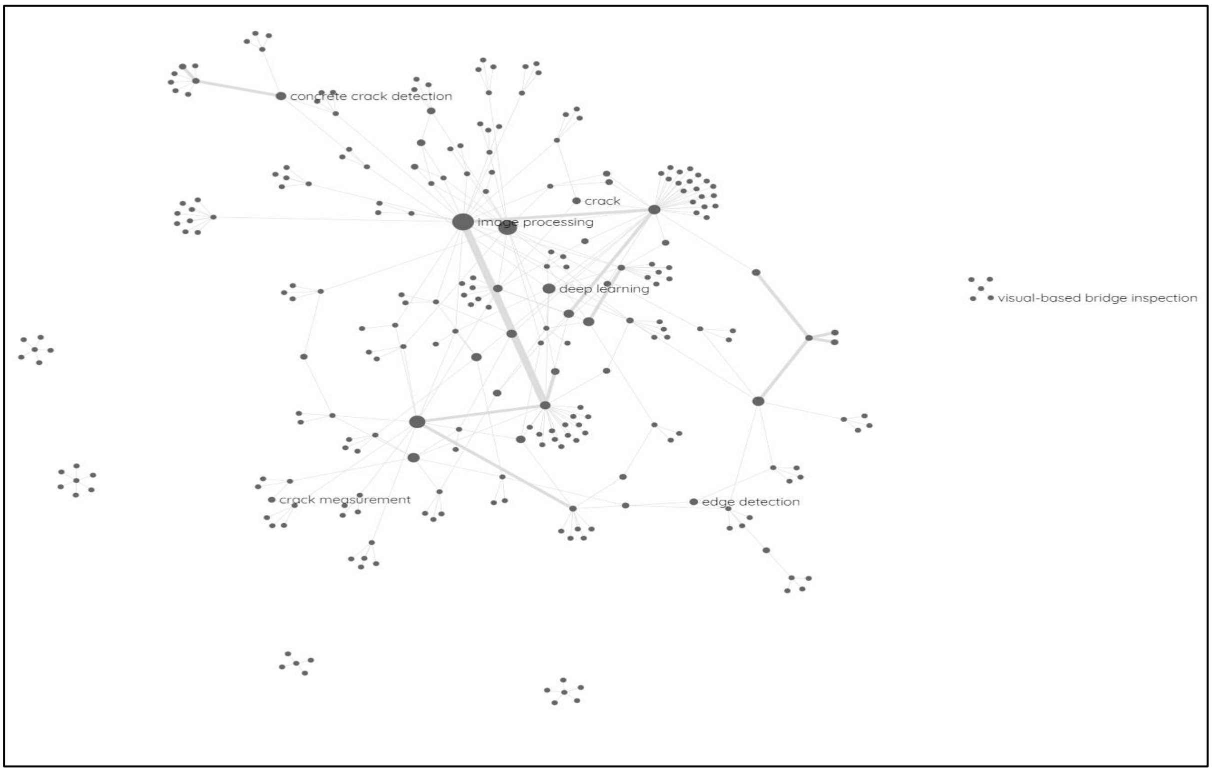


Fig. 17 Authors and source titles co-appearing in the same papers
Source: http://www.scopus.com (accessed on 12th January 2021)

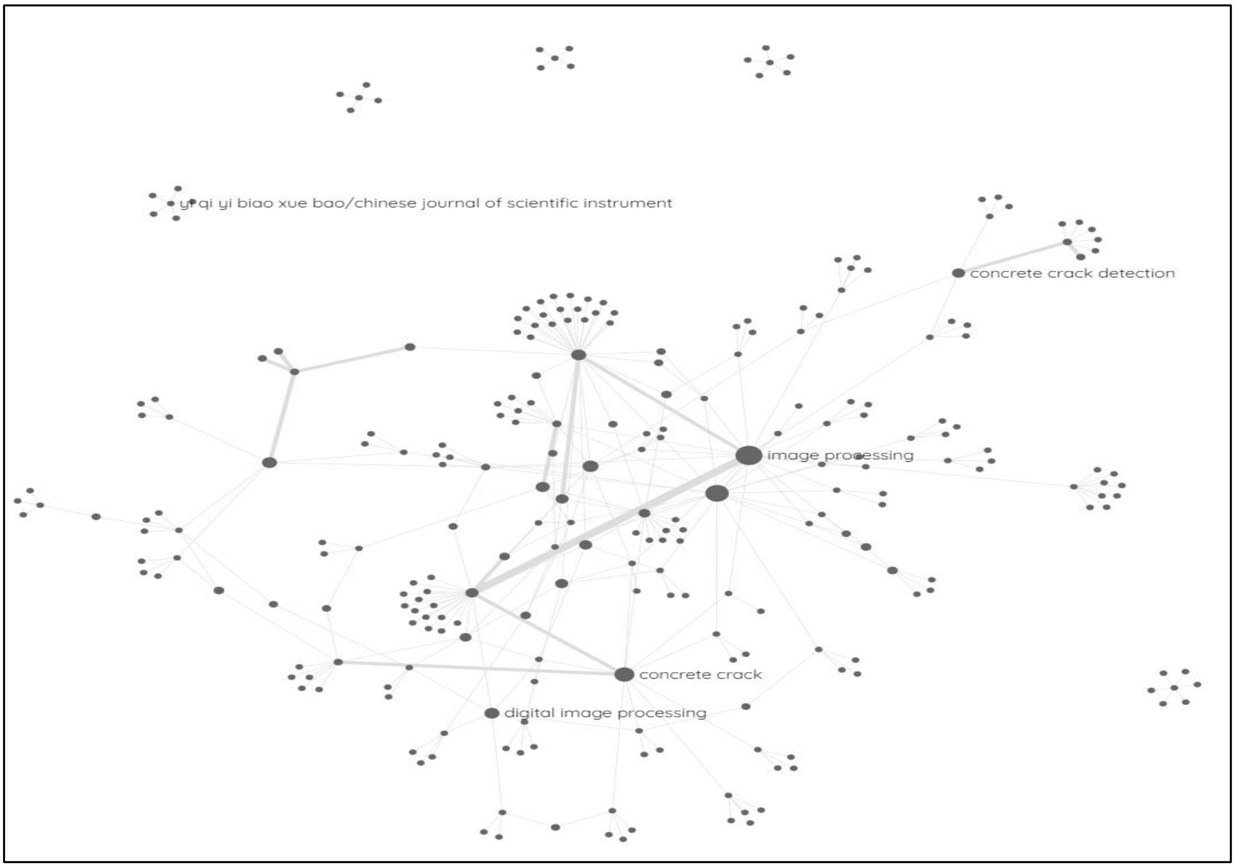


Fig. 18 Source Titles and author keywords co-appearing in the same papers
Source: http://www.scopus.com (accessed on 12th January 2021)

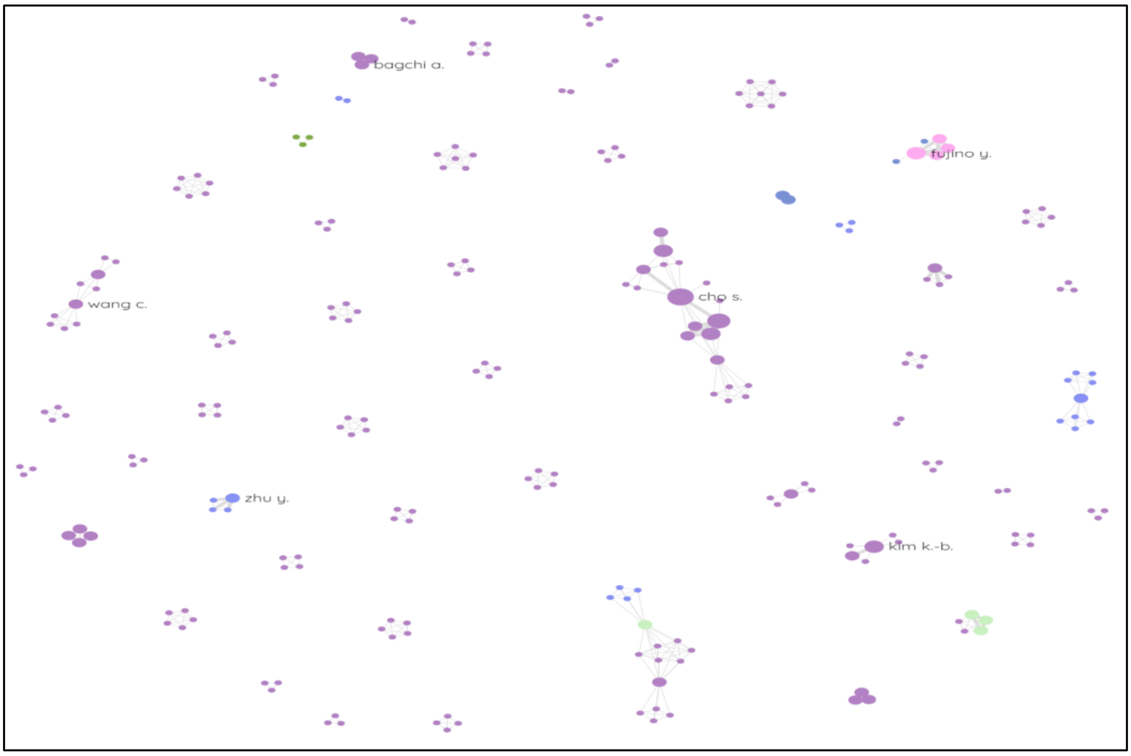


Fig. 19 Authors Linked by Co-Publication

Source: http://www.scopus.com (accessed on 12th January 2021)

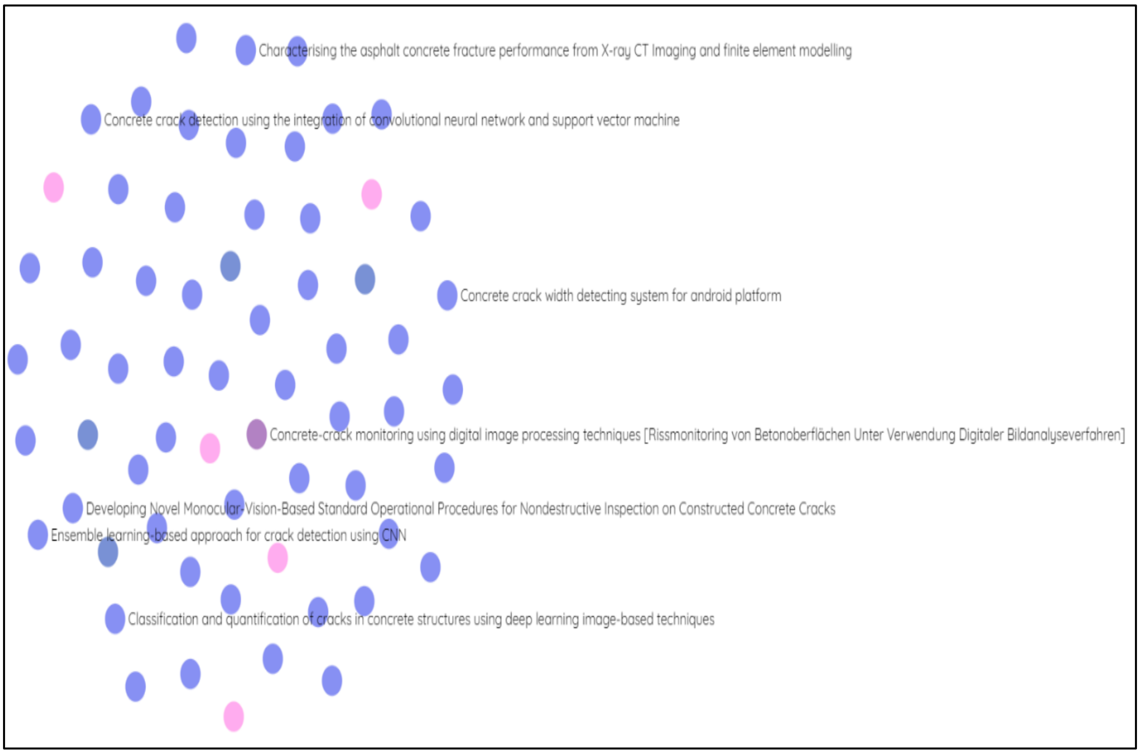


Fig. 20 Papers Linked by Citation (when they have DOI)

Source: http://www.scopus.com (accessed on 12th January 2021)

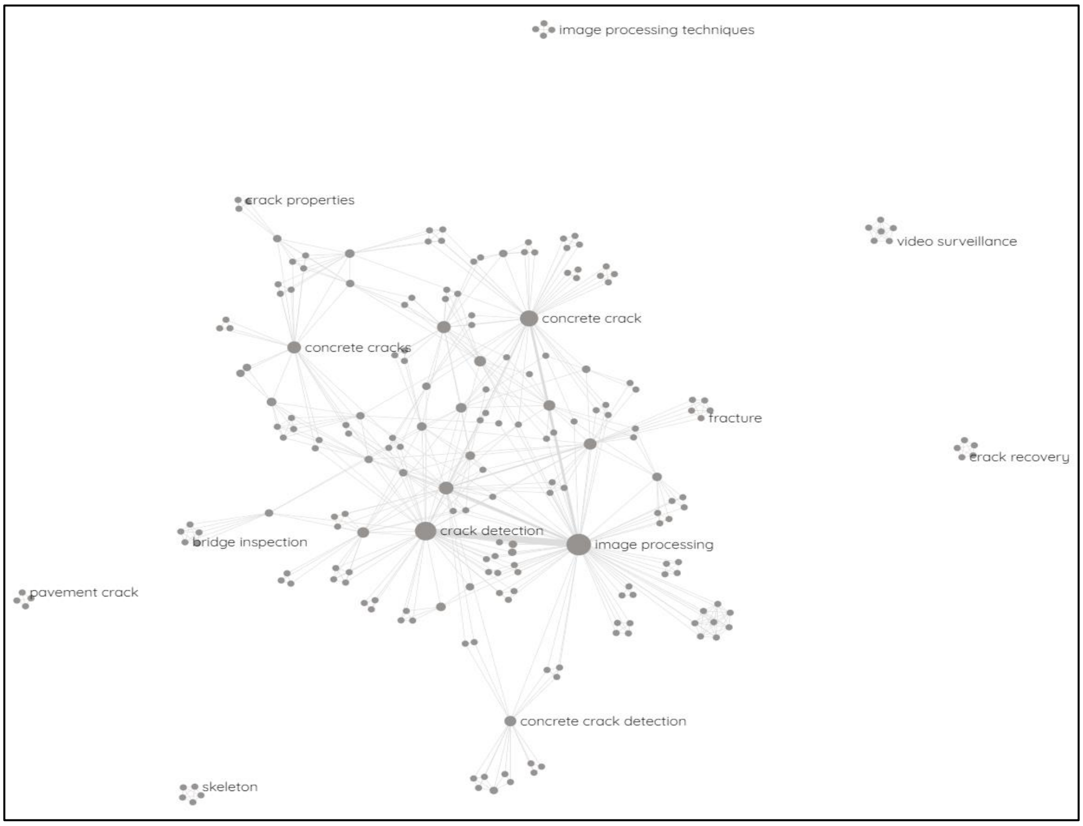


Fig. 21 Author Keywords coappearing in the same papers
Source: http://www.scopus.com (accessed on 12th January 2021)

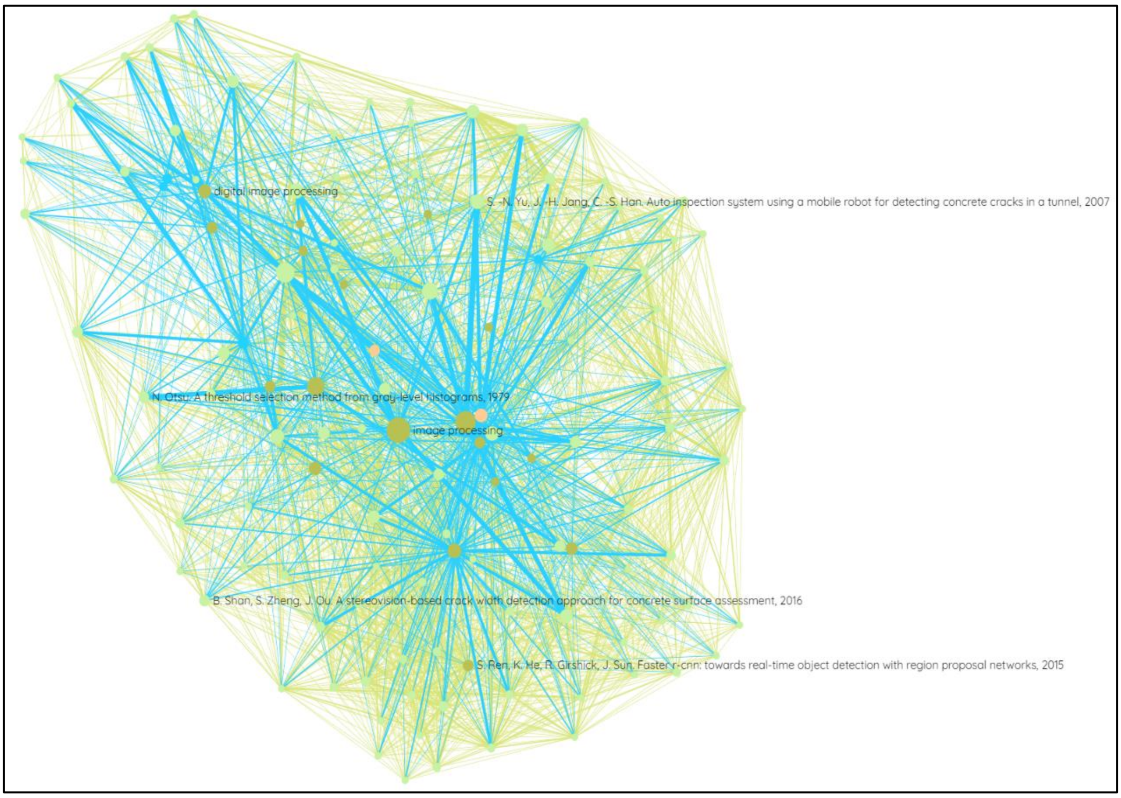


Fig. 22 Reference-scape
Source: http://www.scopus.com (accessed on 12th January 2021)

Table 4: Top Cited Articles

Year	Authors	Title	Source title	Cited by
2017	Cha Y.-J., Choi W., Büyüköztürk O.	"Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks"	Computer-Aided Civil and Infrastructure Engineering	787
2007	Yu S.-N., Jang J.-H., Han C.-S.	"Auto inspection system using a mobile robot for detecting concrete cracks in a tunnel"	Automation in Construction	222
2012	Nishikawa T., Yoshida J., Sugiyama T., Fujino Y.	"Concrete Crack Detection by Multiple Sequential Image Filtering"	Computer-Aided Civil and Infrastructure Engineering	162
2014	Adhikari R.S., Moselhi O., Bagchi A.	"Image-based retrieval of concrete crack properties for bridge inspection"	Automation in Construction	143
2011	Zhu Z., German S., Brilakis I.	"Visual retrieval of concrete crack properties for automated post-earthquake structural safety evaluation"	Automation in Construction	112
2005	Sohn H.-G., Lim Y.-M., Yun K.-H., Kim G.-H.	"Monitoring crack changes in concrete structures"	Computer-Aided Civil and Infrastructure Engineering	70
2013	Lee B.Y., Kim Y.Y., Yi S.-T., Kim J.-K.	"Automated image processing technique for detecting and analysing concrete surface cracks"	Structure and Infrastructure Engineering	66
2017	Kim H., Lee J., Ahn E., Cho S., Shin M., Sim S.-H.	"Concrete crack identification using a UAV incorporating hybrid image processing"	Sensors (Switzerland)	58
2019	Kim H., Ahn E., Shin M., Sim S.-H.	"Crack and Non crack Classification from Concrete Surface Images Using Machine Learning"	Structural Health Monitoring	49
2017	Li G., Zhao X., Du K., Ru F., Zhang Y.	"Recognition and evaluation of bridge cracks with modified active contour model and greedy search-based support vector machine"	Automation in Construction	44
2016	Liu Y.-F., Cho S., Spencer B.F., Fan J.-S.	"Concrete Crack Assessment Using Digital Image Processing and 3D Scene Reconstruction"	Journal of Computing in Civil Engineering	42

Year	Authors	Title	Source title	Cited by
2011	Moon H.-G., Kim J.-H.	"Intelligent crack detecting algorithm on the concrete crack image using neural network"	Proceedings of the 28th International Symposium on Automation and Robotics in Construction, ISARC 2011	37
2010	Caduff D., Van Mier J.G.M.	"Analysis of compressive fracture of three different concretes by means of 3D-digital image correlation and vacuum impregnation"	Cement and Concrete Composites	36
2014	Liu Y., Cho S., Spencer B.F., Jr., Fan J.	"Automated assessment of cracks on concrete surfaces using adaptive digital image processing"	Smart Structures and Systems	34

Source: http://www.scopus.com (accessed on 12th January 2021)

Fig. 17 in addition to the fig. 15 shows that edge detection, crack management, image processing and visual based bridge inspection are also important keywords. Fig. 18 adds digital image processing is also an important keyword. Chienese Journal of Scientific Instrument is also an important source title. Bagchi. A., Chp. S., Zhu. Y., Kim. K. B. are the authors linked by copublication (Fig. 19). If we look at fig. 20 then it gives us an idea about papers which are important from the point of view of considered research topic i.e. they in a way throw light on important techiques need to be considered viz. X-ray CT imagaing with finite element modelling, integration of CNN and SVM, crack detection system using android platform, crack monitoring using digital image processing, ensemble appraoch using CNN and deep learning image based techniques. From fig. 21fracture, crack properties, crack recovery, pavement detection are also keywords which are utilized. Refernce scape in fig. 22 shows image processing and digital image processing are the key teminologies used in the considered references.

5 Research Implications

This study in a way shows that deep learning, image processing, video surveillance are the techniques which are used for the study of concrete cracks. This is in a way revolution in the field of civil engineering. This shows how civil engineering sector and related research are modernizing. Also, from data obtained through Scopus and through network diagram different aspects related to concrete image classification related research are clear. Through paper linked by citations one new dimension about concrete image classification related research is observed that several computer algorithms and combination of them is already worked out by different researchers in order to get an idea about crack properties, fracture, their detection etc. In a way this research paper is an overview of ongoing research related to crack image classification.

6 Conclusion

The classification of the cracks in the concrete surface can be done by using different deep learning models like convolution neural networks with a decent accuracy. The performance of the model can be further enhanced by using variety of filters and noise removal techniques in the initial stages of pre-processing. Different methods of deep learning may also be implemented in order to get the comparison of different results for better understanding of the topic. This fusion of computer science techniques over a civil engineering problem will in a mitigate problems related to concrete structures. This research paper shows that there is scope of research for concrete image classification in India, Indian universities and research centres can use the AI and ML techniques discussed in this paper, this will in a way lead to the improvisation of the existing processes related to the undertaken research.

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