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Analyzing Real-Time Surveillance Video Analytics: A Comprehensive Bibliometric Study

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Abstract: The purpose of this study is to anlalyze, identify and quantify the scope of research on real time surveillance video analytics (RTSVA), and to expose the study trends, development, and evolution in the SCOPUS database. An electronic search was used to find the most relevant articles. The studies for examination were obtained from the Scopus database. With the help of the R programming language and VOSviewer software, each composition was analyzed in various dimensions such as co-authorship, co-citation, conceptual structure, co-word occurrence, trend topics analysis, thematic map, and visualization analysis. Using strategic thematic maps we highlighted motor themes (edge computing, video analysis and deep learning), niche(autonomous vehicles, and block chain), basic(IoT, bandwidth and data handling) and emerging themes(mobile computing and learning models). RTSAV literature has evolved greatly over the previous decade, according to the research. Future researchers may refer to it. Using relation methods such as co-word, co-author, co-citation, bibliographic coupling and thematic map analysis revealed potential research areas in this study. The relational word cloud analysis shows that video analytics and deep learning are the two **crux** that connects to other frequently keywords in the study. A thorough review and meta-analysis would assist future scholars to develop a robust theoretical foundation. Scopus database was used for science mapping in this research. This study may assist new and existing researchers in identifying new research areas, appropriate sources and cooperation prospects, as well as making informed judgments. Findings related to evaluative and relational methods may aid novice researchers.

Keywords: *Bibliographic coupling analysis, tree map, thematic maps, video analytics, and word analysis,*

1. Introduction

There is a rising interest in integrating new Internet of Things (IoT) technology into cities to create sensor arrays that collect data on environmental conditions and human influence. This can be utilized to improve the livability of the city and the welfare of its residents. Utilizing embedded vision sensors to collect information on pedestrian and vehicle density and traffic flow is a popular area of research. This information can be utilized in a variety of ways to improve traffic navigation and public safety. For instance, it can be superimposed on top of maps to **ease** route planning around congested areas or to avoid isolating walkways. It can also detect pedestrian surges (e.g., near subway stations when a train releases a stream of passengers) to better control the timing of traffic signals and accommodate the rush in a safe manner [1]. Additionally, traffic jams, road construction, etc., and even when we get to our location, the worry is not over: the quest for a parking spot has just begun. For example, [9] indicates that in a small commercial area of Los Angeles, a driver spends an average of 3.3 minutes searching for a parking spot, so adding around 2.5 miles to the journey. This is a problem not only for those particular drivers but for everyone: in addition to causing additional traffic from drivers searching for parking, it impacts everyone [2]

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Understanding and interpreting the content of big video archive collections have remained a time-consuming and arduous procedure. In addition to the massive size of modern archives and the challenges that semantically-sensitive image retrieval has faced over the past two decades, the lack of sufficient metadata and a lack of a precise understanding of the archive's actual content are additional obstacles to effectively analyzing video archives with existing methods. A fourth challenge is the inadequacy of translation across semiotic registers; words can never fully represent sounds and visuals, leaving a meaning gap when labels alone are used to describe and seek information [3].

The expansion of the Internet of Things (IoT) is creating unprecedented access to observational data regarding physical infrastructure, such as traffic surveillance cameras and smart power meters in Smart Cities, as well as a social lifestyle through fitness bands such as Fitbit and automation assistants such as Google Home. These data streams are combined with historical data and analytic models to make intelligent decisions, such as managing traffic signaling or optimizing the electricity grid in cities, or controlling devices in your home. Due to the Cloud's easy service-oriented access to ostensibly endless resources, all of this decision-making and analytics have traditionally occurred there. Edge devices and sensors transmit data to the data center, while Cloud analytics communicate control decisions back to the edge for execution. However, this has significant disadvantages. The network capacity necessary to transmit high-definition video streams to the Cloud can be prohibitive, as can the round-trip delay required to convey data from the edge to the Cloud and control signals back. Clouds also offer a pay-as-you-go pricing model in which data transfers, computing, and storage are billed separately [4].

Existing edge computing-based video analytics solutions lower the bandwidth burden and latency during video transmission, hence enhancing the Quality of Service in comparison to the cloud computing approach (QoS). However, our research focuses on the difficulties and flaws of edge computing-based video analytics systems. In an edge video analytics system, video data transmission is unidirectional (from the camera to the end user); thus, the end user cannot operate the video analytics process elastically in response to real-time needs. In our study, this issue is identified as Problem C1. It is tough to automatically choose the video data in a region of interest (ROI) in a video stream when the end user controls the video content. This instance is known as the second issue (C2). The network circumstances are crucial for the transmission of video data because the aforementioned advantages cannot be realized if Elastic Edge does not adapt to bad network conditions. Due to inadequate network bandwidth, the quality of the video service cannot meet user expectations. We refer to this difficulty as Problem C3 in our study. To enable end users to control video material in real-time, the user's ROI must be identified. To convey valuable data based on the user's preference, we must take into account the network's dynamic conditions and application needs [5]

Mobile devices such as vehicles and smartphones are constantly generating a massive amount of data, which could be utilized for machine learning in a bid to achieve smart mobile applications. However, transmitting private data to a centralized or an edge server for training may lead to privacy issues and could cause long communication latency and large resource costs [1]. A decentralized machine learning approach called Federated Learning (FL) has been proposed by Google that enables cooperative learning on devices without sharing the local data [2]. Clients train the model on-device in a privacy-preserving manner using their local datasets and transfer the local model parameters to the FL server for aggregation. As a result, FL enables user privacy preservation, low communication costs, and transmission latency reduction owing to transmitting only model parameters to the server for aggregation. Furthermore, in time-critical systems such as autonomous vehicles, making real-time decisions locally at end devices significantly decreases response time [6].

As 5G communications systems, 4K network cameras, and portable virtual reality (VR) devices increase, both household and commercial consumers are destined to receive unprecedentedly high-definition video services, which will provide a plethora of new business opportunities. business possibilities. According to the Cisco visual networking index, video data traffic will treble by 2022, accounting for 82% of all Internet data traffic. The dominant traffic of video services will encounter a bottleneck in the underlying communication infrastructures. Moreover, mobile video traffic has nearly tripled in the previous decade, but network capacity has increased by only tenfold. The outdated cellular infrastructure can no longer support the skyrocketing data demand from video streaming. Future communications systems will be required to figure out how to efficiently transmit the exponentially expanding video data. To achieve intelligent and secure data delivery in video-centric networks (VCNs), 5G wireless communications must fully leverage pervasive connections and collaborate with potent cyber-security technologies to enhance logical links with inter-node trust, offload backhaul traffic, and protect users' identity privacy [7].

Due to developments in Internet of Things (IoT) technology, there has been a significant increase in the transfer of massive amounts of video data to the cloud for video analysis. This cloud-based video analytics places a large demand on the network and increases latency, making it difficult to meet user delay requirements. As a result, edge computing has arisen as a new computing paradigm to enhance the performance of video analytics. Widespread usage of edge video analytics in industrial automation, smart campuses, and smart linked vehicles [8].

computing that is both loud and mobile. As a result of the convergence of these two developments, cloud-based back-ends are used to deliver services that cannot operate natively on mobile devices. As mobile devices increase in storage and processing capacity in line with Moore's Law, services increase in sophistication and complexity at the same rate, assuring that high-end apps like augmented reality and 3D gaming will continue to need a cloud-based backend. A cloud-based backend, however, has slowness when the cloud is far from the end-user and is not immune to network and connection failures [9]

As it delivers computing resources of edge nodes, the growing Internet of Things (IoT) with edge computing technology becomes more tempting to allow video analytics at scale (e.g., embedded devices). There are three benefits of processing video frames at edge devices as opposed to transferring them to the cloud data center: 1) decreasing service response time and enhancing situational awareness, as local edge execution of MOT is only one hop away; 2) minimizing the impact of unpredictable network communications; and 3) conserving bandwidth resources from edge to cloud if more vision-based activities are completed at edge nodes. Consequently, a cost-effective real-time MOT strategy is required for low-latency video analytics on edge-embedded devices, given the resource-constrained nature of edge nodes [3].

This paper determines to review research in the Real-Time Surveillance Video Analytics field and its insights and overview through science mapping review methodology. This paper addresses the following research questions:

R.Q. 1: What are key growth trends in research on Real-Time Surveillance Video Analytics?

RQ 2: Which authors, institutions, and journal articles from emerging regions have significantly influenced Real-Time Surveillance Video Analytics research over the past 25 years?

R.Q. 3: What does the social structure of the knowledge base have on Real-Time Surveillance Video Analytics?

R.Q. 4: What topics in the Real-Time Surveillance Video Analytics literature have been studied with the most significant frequency and are currently attracting the most incredible attention?

The above research questions decode into the following research objectives.

1. To know the evolution, progress, or patterns in knowledge development on Real-Time Surveillance Video Analytics

2. To identify knowledge gaps and to originate novel ideas for further investigation in Real-Time Surveillance Video Analytics.

2. Methods

In this study we used the Scopes dataset to get the research data, after we search via keywords and select the inclusive criteria we reach 345 (study see table1), then we used Microsoft Excel to clean our data set, and after that, we used R Programming Studio software and VOSviewer software to get our results, see figure 1.

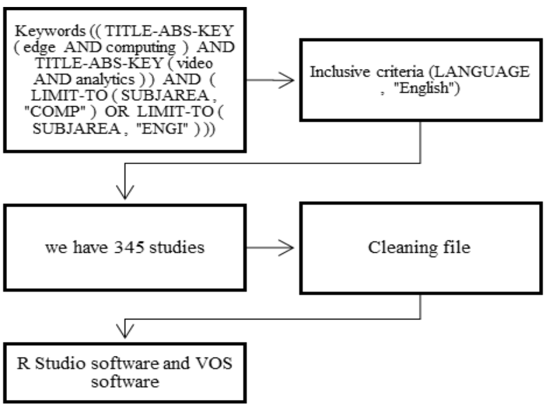

Fig 1: Methodological flowchart of analysis

Table 1. Study criteria

	Criteria
Open Access	All Open Access, Gold Hybrid Gold, Bronze, Green
Years	From 2012 to 2023
Subject area	COMP & ENGI
Language	English

Query Strings:

(TITLE-ABS-KEY (edge AND computing) AND TITLE-ABS-KEY (video AND analytics)) AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA , "ENGI")) AND (LIMIT-TO (LANGUAGE, "English"))

The selected manuscripts that met the inclusion criteria were exported in CSV format and converted into VOSviewer software and an R Package data frame using the Open-Source R Programming Package BIBLIOSHINNY to achieve precise findings.

Using the dimensionality-reduction approach, the quantity of data in the data set that was unrelated to the research was removed. Through extensive network mapping of those filtered data, the V.O.S. viewer and Biblioshiny from the R package assisted with data visualization, parameter filtering, and the construction of the data's social structures.

To reach our objectives we apply Main information, authors, document, topic trends, cluster affiliation, and journal analysis via using R Programming Package & VOSviewer software's.

3. Results & Discussion

The main results in this study in table 2 we demonstrate the time span, document counts, and authors' details, in this paper we have 302 documents and the annual growth rate is 19.35%, while the document Average Age is 2076, and the average citations per doc are 10.43. from the keywords aspect, we have 754 keywords and 976 authors. In the same way, 4.51 is co-Authors per document and 27.48% are international co-authorships.

Table 2. Main information of the data.

Description	**Results**
Timespan	2012:2023
Sources (Journals, Books, etc)	203
Documents	302
Annual Growth Rate %	19.35

Document Average Age	2.76
Average citations per doc	10.43
References	9099
DOCUMENT CONTENTS:	
Keywords Plus (ID)	2045
Author's Keywords (DE)	754
AUTHORS	
Authors:	976
Authors of single-authored docs	5
AUTHORS COLLABORATION	
Single-authored docs	6
Co-Authors per Doc	4.51
International co-authorships %	27.48

In figure 2 we illustrate the annual production for Real-Time Surveillance Video Analytics, as we can observe from table 3 the first articles published in this field start in 2012, but the real production started from 2017 and stile increased till 2023, from 2012 to 2013 we have just one publication per year, whereas, from 2015 till 2017 the publication increase from 2 papers to 13 papers. In addition, the publication from 2018 to 2022 develops from 28 papers to 78 papers

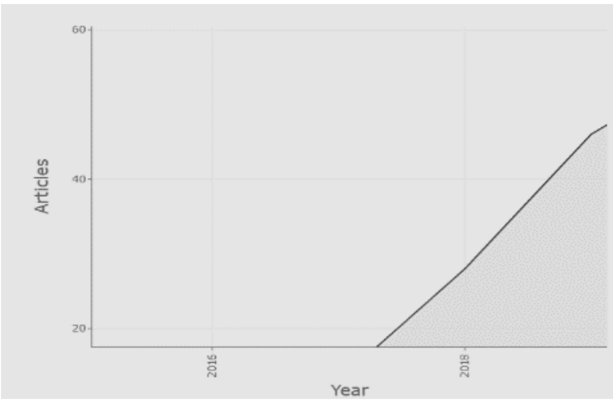

Fig 2. Annual production

Table 3: Annual production detail

Year	Articles
2012	1
2013	1
2015	2
2016	2
2017	13
2018	28
2019	46
2020	56
2021	68
2022	78
2023	7

Figure 3 demonstrates the average citation per year, as we can see the average citation start from 2012 with 2 citations, while from 2014 to 2016 we have the largest citation quantity with 20 citations per year. From 2016 to 2018 the citation was not stable, and from 2018 to 2020 the citation start to decrease gradually from 5 citations to 2 citations per year, and finally the citation decrees from 2 citations to 1 citation during 2020-2022.

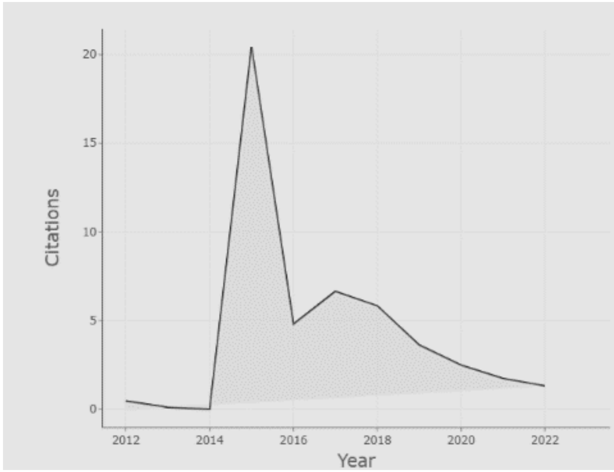

Fig3. Average citation per year

3.1 Sources analysis:

In figure 4 we demonstrate the most effective resources in Real-Time Surveillance Video Analytics, as we can see the IEEE INTERNET OF THINGS JOURNAL, ACM INTERNATIONAL CONFERENCE PROCEEDING SERIES, IEEE ACCESS, LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS), PROCEEDINGS - IEEE INFOCOM, IEEE INTERNATIONAL CONFERENCE ON COMMUNICATIONS, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, PROCEEDINGS - 2018 3RD ACM/IEEE SYMPOSIUM ON EDGE COMPUTING, and SEC 201, PROCEEDINGS - INTERNATIONAL CONFERENCE ON DISTRIBUTED COMPUTING SYSTEMS, have the significant influence on this field, see table 4.

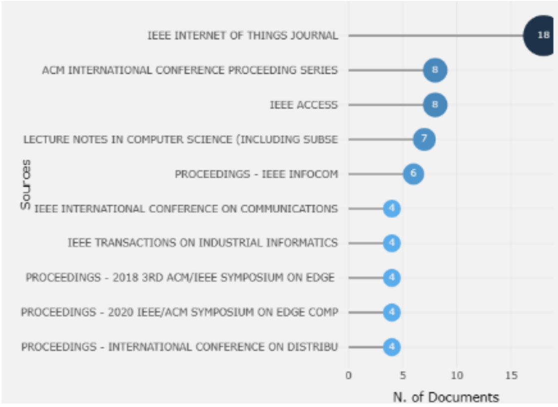

Fig 4. Most relevant source

Table 4: Most Relevant Sources detail

Sources	Articles
IEEE INTERNET OF THINGS JOURNAL	18
ACM INTERNATIONAL CONFERENCE PROCEEDING SERIES	8
IEEE ACCESS	8
LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS)	7
PROCEEDINGS - IEEE INFOCOM	6
IEEE INTERNATIONAL CONFERENCE ON COMMUNICATIONS	4
IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS	4
PROCEEDINGS - 2018 3RD ACM/IEEE SYMPOSIUM ON EDGE COMPUTING, SEC 2018	4
PROCEEDINGS - 2020 IEEE/ACM SYMPOSIUM ON EDGE COMPUTING, SEC 2020	4
PROCEEDINGS - INTERNATIONAL CONFERENCE ON DISTRIBUTED COMPUTING SYSTEMS	4

According to Bradford's Law of scattering, it consists of three-level zones. These zones form approximately a geometric series in the form of 1:n:n 2 . in the first zone we have IEEE INTERNET OF THINGS JOURNAL, ACM INTERNATIONAL CONFERENCE PROCEEDING SERIES, IEEE ACCESS, LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS), PROCEEDINGS - IEEE INFOCOM. While the second zone contains COMMUNICATIONS IN COMPUTER AND INFORMATION SCIENCE, EDGE COMPUTING, HOTEDGEVIDEO 2021 - PROCEEDINGS OF THE 2021 3RD ACM WORKSHOP ON HOT TOPICS IN VIDEO ANALYTICS AND INTELLIGENT EDGES, HOTMOBILE 2021 - PROCEEDINGS OF THE 22ND INTERNATIONAL WORKSHOP ON MOBILE COMPUTING SYSTEMS AND APPLICATIONS, 2020 IEEE 23RD INTERNATIONAL CONFERENCE ON INTELLIGENT TRANSPORTATION SYSTEMS, ITSC 2020. In the third zone, we have WORLD AUTOMATION CONGRESS PROCEEDINGS WIRELESS COMMUNICATIONS AND MOBILE COMPUTING, USENIX WORKSHOP ON HOT TOPICS IN EDGE COMPUTING, HOTEDGE 2018, CO-LOCATED WITH USENIX ATC 2018, SYSCON 2019 - 13TH ANNUAL IEEE INTERNATIONAL SYSTEMS CONFERENCE, PROCEEDINGS, SOFTWARE - PRACTICE AND EXPERIENCE, and SOCC 2019 - PROCEEDINGS OF THE ACM SYMPOSIUM ON CLOUD COMPUTING journals, to same up we can say the first zone represent the best 25 journals, and the second zone represents 80 journals. While the less quality 89 journals represent in zone 3, The summary of the divisions of the nucleus is given below.

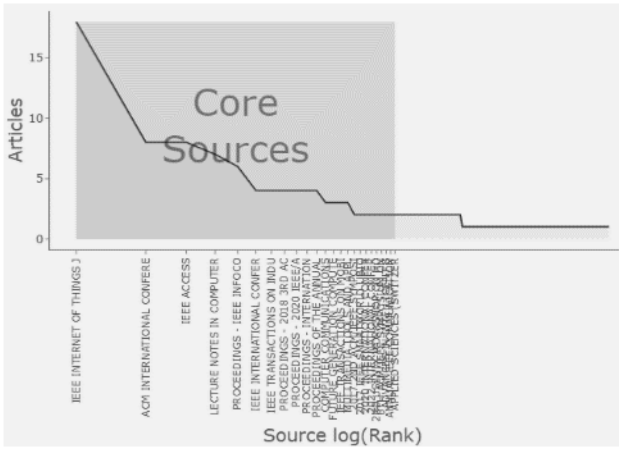

Fig 5. Source clustering through Bradford's Law

Table 5: Source clustering through Bradford's Law details

Zone	Quantity
1	25
2	80
3	89

3.2 Authors

In this analysis we will explain the top authors in the Video Analytics field as we can see ZHANG Q, CALYAM P, CHEN Y, WANG J, KHOCHARE A, PILLAI P, QU C,

SATYANARAYANAN M, SHI W, SIMMHAN Y, WANG J, KHOCHARE A, PILLAI P, QU C, SATYANARAYANAN M, SHI W, SIMMHAN Y, WANG S, ZHANG X, ANANTHANARAYANAN G, are the best ten authors in this area. While ZHANG S, SHU Y, LIU Y, JIANG J, CAO G, BAHL P, ZHONG H, WANG Z, WANG Y, and WANG X are the less relevant authors in this field. See figure 6 and table 6.

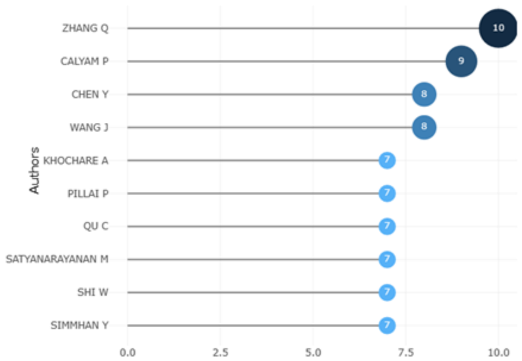

Fig 6. Most relevant author

Table 6: Local citation author

Authors	Articles
ZHANG Q	10
CALYAM P	9
CHEN Y	8
WANG J	8
KHOCHARE A	7
PILLAI P	7
QU C	7
SATYANARAYANAN M	7
SHI W	7
SIMMHAN Y	7
WANG S	7
ZHANG X	7
ANANTHANARAYANAN G	6
LEE J	6
SUN H	6
WANG X	6
WANG Y	6
WANG Z	6
ZHONG H	6
BAHL P	5
CAO G	5
JIANG J	5
LIU Y	5
SHU Y	5
ZHANG S	5

3.3 Authors' Production over Time

In figure 7 we demonstrate the authors' production for every year from 2015 to 2023, as we can observe in table 7 CALYAM P have a large amount of citation from 2017 tile 2023, based on this analysis we can say CALYAM P is the best author during last five years

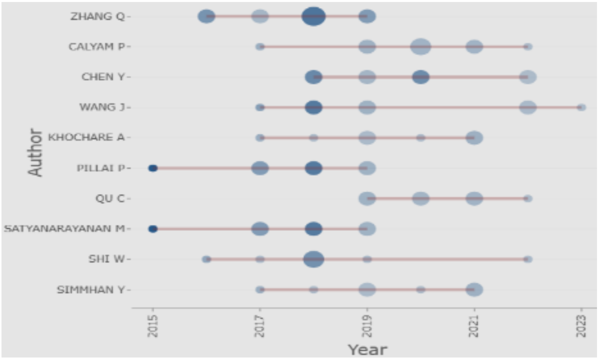

Fig 7. Author's production over time

Table 7 Authors' Production over Time in details

Author	year	Frequency	TC	TC pY
CALYAM P	2017	1	30	4.286
CALYAM P	2019	2	18	3.6
CALYAM P	2020	3	12	3
CALYAM P	2021	2	9	3
CALYAM P	2022	1	0	0
CHEN Y	2018	2	107	17.833
CHEN Y	2019	2	12	2.4
CHEN Y	2020	2	67	16.75
CHEN Y	2022	2	0	0
KHOCHARE A	2017	1	30	4.286
KHOCHARE A	2018	1	1	0.167
KHOCHARE A	2019	2	2	0.4
KHOCHARE A	2020	1	0	0
KHOCHARE A	2021	2	12	4
PILLAI P	2015	1	319	35.444
PILLAI P	2017	2	81	11.571

PILLAI P	2018	2	140	23.333
PILLAI P	2019	2	18	3.6
QU C	2019	2	18	3.6
QU C	2020	2	9	2.25
QU C	2021	2	9	3
QU C	2022	1	0	0
SATYANARAYANAN M	2015	1	319	35.444
SATYANARAYANAN M	2017	2	81	11.571
SATYANARAYANAN M	2018	2	140	23.333

3.4 Country Scientific Production

In this analysis, we demonstrate the top countries published in the video analysis field, as we can observe USA, China, Canada, the UK, SOUTH KOREA, AUSTRALIA, CANADA, ITALY, SPAIN, and IRELAND are the best counties in this stream with 483, 293, 74, 50, 45, 41, 37, 33, 29, and 28 frequency. Whereas, TURKEY, THAILAND, SWITZERLAND, NORWAY, ETHIOPIA, EGYPT, BELGIUM, MALAYSIA, KAZAKHSTAN, ESTONIA, SWEDEN, INDONESIA, SINGAPORE, PORTUGAL, NETHERLANDS, and QATAR are the fewer countries productive in the video analysis field. See figure 8 and table 8.

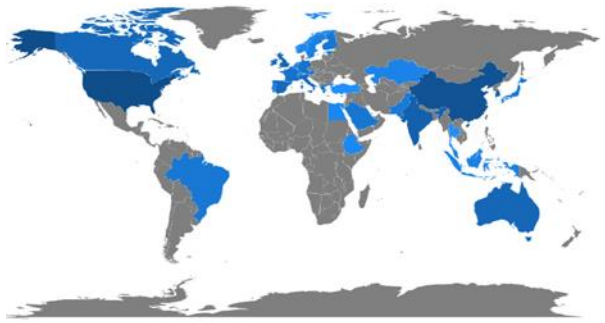

Fig. 8. Country production

Table 8: Country production frequency

Region	**Frequency**
USA	483
CHINA	293
INDIA	74
UK	50
SOUTH KOREA	45
AUSTRALIA	41
CANADA	37
ITALY	33
SPAIN	29
IRELAND	28

3.5 Keywords

In this section, we applied document analysis to explore the keyword frequency and investigate what is the key words trend in the video analysis field. For the most frequency keyword as we can see in table 9 edge computing, video analytics, deep learning, cloud computing, internet of things, IoT, mobile edge computing, computer vision, computation offloading, and fog computing are the most frequency keywords

Fig. 9. Word cloud

Table 9: Keywords frequency

Terms	Frequency
EDGE COMPUTING	149
VIDEO ANALYTICS	70
DEEP LEARNING	24
CLOUD COMPUTING	21
INTERNET OF THINGS	18
IOT	15
MOBILE EDGE COMPUTING	13
COMPUTER VISION	12
COMPUTATION OFFLOADING	11
FOG COMPUTING	11

3.6 Tree Map

In Figure 10 we have a Tree Map depicting the most significant author-word dynamics concerning this study. The Word Dynamics Tree Map illustrates the major themes and shifting tendencies of the text. To investigate current hot subjects in the area, this is a must-have resource. A tree map incorporates a set of numerical values representing a range of dimensions. The structure will be defined by the values in the dimensions.

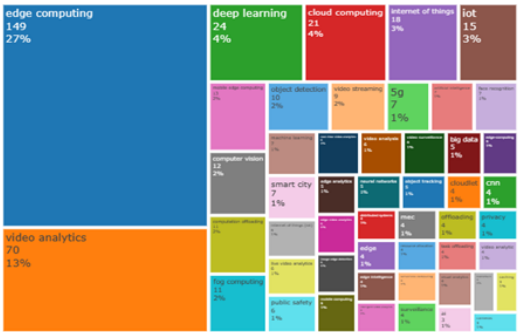

Fig. 10. Tree map

3.7 Trend topic

In this analysis, we determine the trend topics in the video analysis field, as we can observe in figure 11 the most trend topics between 2017 to 2022 are artificial intelligence with 7 frequencies, 5G with 7 frequencies, object detection with 10 frequencies, deep learning with 24 frequencies, video analytics with 70 frequency, edge computing with 148 frequency, machine learning with 7 frequency, IoT with 15 frequency, cloud computing with 21 frequency, video analysis with 6 frequency, video streaming with 9 frequency, computation offloading with 11 frequency, public safety with 6 frequency, and face recognition with 7 frequency

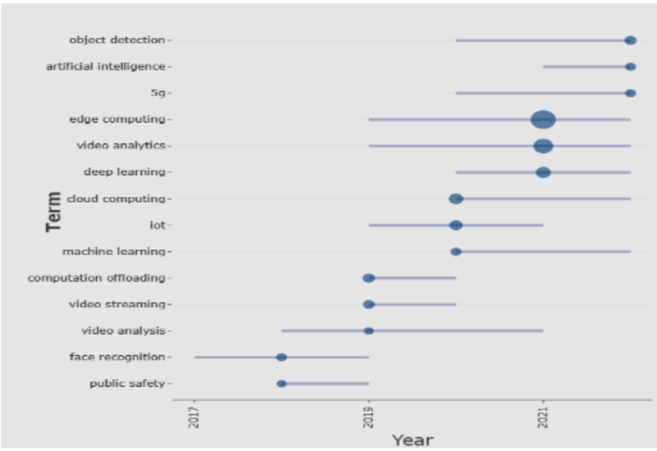

Fig. 11. Trend topics based on author's keywords

Table 10: Topic trend in details

item	freq	year_q1	year_med	year_q3
face recognition	7	2017	2018	2019
public safety	6	2018	2018	2019
computation offloading	11	2019	2019	2020
video streaming	9	2019	2019	2020
video analysis	6	2018	2019	2021
cloud computing	21	2020	2020	2022
iot	15	2019	2020	2021
machine learning	7	2020	2020	2022
edge computing	148	2019	2021	2022
video analytics	70	2019	2021	2022
deep learning	24	2020	2021	2022
object detection	10	2020	2022	2022
5G	7	2020	2022	2022
artificial intelligence	7	2021	2022	2022

3.8 Thematic Map

A thematic map concentrates on the spatial variability of a specific theme, in a thematic map we have four corners and each corner represents different kinds of themes, those themes are classified based on four criteria (see figure 12): Niche themes, Motor themes, Basic themes, and Declining themes.

Niche themes: in this quadrant, we represent the extremely developed themes but not essential to the research field, in niche themes we have four themes: vehicles, automation vocals, blockchain.

Motor themes: in this quadrant, we demonstrate the most developed themes in this area. The following themes are edge computing, video analysis, and deep learning.

Basic and transverse themes: in this quadrant, we display not developed themes in this field. The following key themes are the internet of things, bandwidth, and data handling.

Declining themes: in this fourth quadrant we represent not relative and not developed themes to this stream. They are falling, or emerging themes are finding their feet and require further investigation, in the declining corner we just have the mobile computation, and learning model.

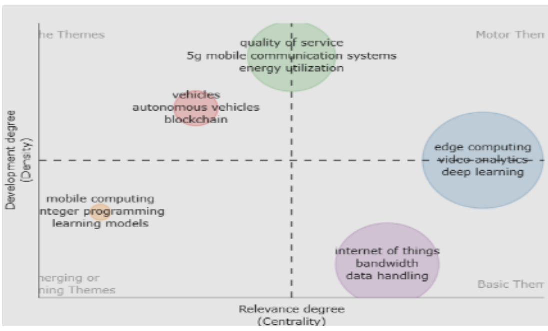

Fig. 12. Thematic Map

Table 12: Thematic map cluster

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
edge computing	5.691009	43.21105	21	6	501
computation offloading	0.409848	52.20779	16	15	28
mobile edge computing	0.770431	39.67872	18	5	42
video analysis	1.284722	34.20139	19	3	17
video compression	0	50	4.5	11	5
real-time video analytics	1.891667	90.61111	20	20	56
5g	0.227551	47.61905	11	7	13
drone video analytics	0.111111	38.88889	9.5	4	6
cloudlet	0.25	66.66667	13.5	17	8
video signal processing	0	75	4.5	18.5	6
resource efficiency	0	50	4.5	11	2
scalability	0	50	4.5	11	2
mobility	0	75	4.5	18.5	4
video processing	0	50	4.5	11	2
data analytics	0.25	50	13.5	11	2
approximate computing	0.25	62.5	13.5	16	4
big data platform	0	100	4.5	21	6
energy consumption	0.555556	33.33333	17	1.5	3
multi-access edge computing	0.111111	33.33333	9.5	1.5	3
collaboration	0.25	50	13.5	11	2
microservices	0	50	4.5	11	2

3.9 Co-occurrence author keywords

In this section we will try to illustrate the keywords co-occurrence analysis as we can see in figure 15 we have four basic nodes and every node represents a different color, each node of the network represents a keyword and the basis nods are edge computing in red color, video analysis purple color, internet of thing in yellow color, and cloud computing in green color. Every node indicates the occurrence of the keyword, in the video analysis field, as we can see edge computing shows high co-occurrence with the internet of things, deep learning, video analysis, and public safety. In addition, there is a significant relationship between video analysis, deep learning, cloud coupling, and resource allocation. While the is less link between real-time video analysis, image edge detection, visual analytics, and object tracking.

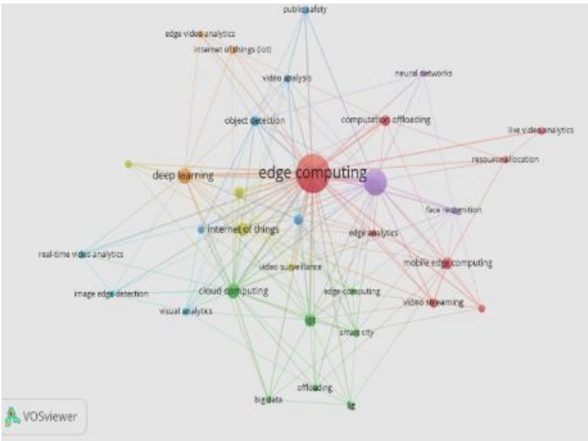

Fig. 13. Co-occurrence author keywords

3.10 Citation analysis Country

In this analysis we will demonstrate the link between the country, The link among the nodes appears as the relationship between authors, so the thickness of the link signals the occurrence of citations between the authors, consequently, the thicker line represents the strong relationship among the authors, while the thinner line represents the weak relationship between the authors, as we can see there is a high link between USA with Canada, UK, China, France, and Ireland. Although, there is an insignificant relationship between South Korea, Australia, Ireland, Taiwan Hong Cong, and Canada.

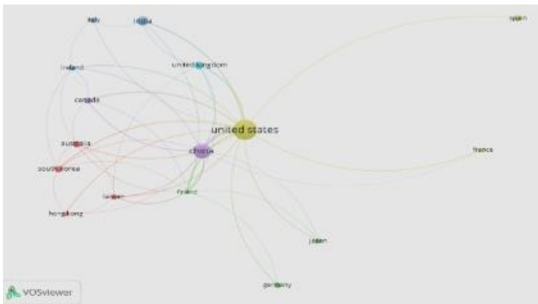

Fig. 14 Citation analysis

3.11 Bibliographic coupling analysis

Bibliographic coupling analysis assists to illustrate the related subject between sources, authors, documents, organizations, and countries. In our analysis, we will concentrate on sources analysis. Bibliographic coupling sources analysis: this analysis will explain how many journals are working on competitive strategy and organizational performance. As we can see in figure 16 we have so many journals that have the same interest in this area, for instance, USA, UK, Canada, and China have the same interest in this topic

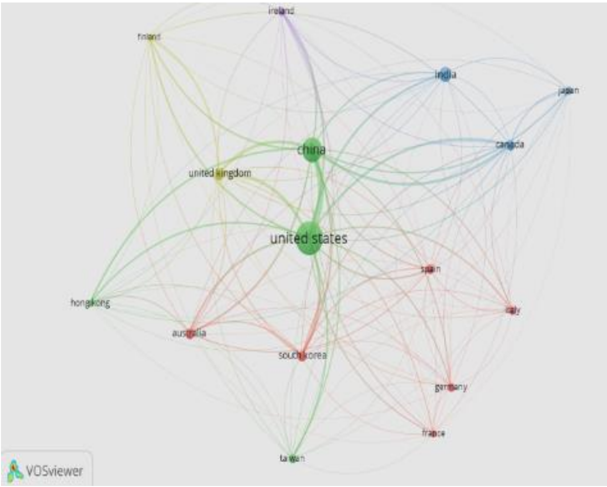

Fig. 15 Bibliographic coupling

Table 11: Collaboration network

Node	Cluster	Betweenness	Closeness	PageRank
USA	1	143.3319	0.021277	0.147413
CHINA	1	68.63413	0.018519	0.142168
INDIA	1	35.63616	0.016667	0.039176
UNITED KINGDOM	1	19.49163	0.017857	0.053313
CANADA	1	9.823166	0.015385	0.030961
HONG KONG	1	0	0.014706	0.022584
FRANCE	1	67.67029	0.018182	0.032782
FINLAND	1	28.62192	0.015152	0.026282
JAPAN	1	0.724359	0.014085	0.021264
SWEDEN	1	0	0.013158	0.009819
ESTONIA	1	0	0.011364	0.008017
BELGIUM	1	0	0.013699	0.013525
SWITZERLAND	1	0	0.013333	0.007245
KOREA	2	7.652928	0.016667	0.027189
AUSTRALIA	2	26.59366	0.017857	0.041194
ITALY	2	12.36899	0.015152	0.024137
SPAIN	2	56.59062	0.018182	0.041569
GREECE	2	3.406494	0.013514	0.016441
BRAZIL	2	0	0.013699	0.018598
PAKISTAN	2	23.00451	0.014706	0.024456
ETHIOPIA	2	0	0.012821	0.012324
SINGAPORE	3	28	0.014286	0.01804
THAILAND	3	0	0.010204	0.009799
GERMANY	4	59.67936	0.013699	0.039558
SAUDI ARABIA	4	10.04574	0.011628	0.0214

While the is less link between real-time video analysis, image edge detection, visual analytics, and object tracking. And we demonstrate the link between the country, The link among the nodes appears as the relationship between authors, so the thickness of the link signals the occurrence of citations between the authors, consequently, the thicker line represents the strong relationship among the authors,

while the thinner line represents the weak relationship between the authors, as we can see there is a high link between USA with Canada, UK, China, France, and Ireland. Although, there is an insignificant relationship between South Korea, Australia, Ireland, Taiwan Hong Cong, and Canada.

4. Conclusion

The study carried out a comprehensive bibliometric literature review on insights into financial literacy. The following paragraphs discuss the findings in brief. The study was initiated by importing the data by reverse keywords, In this study, we used the Scopes dataset to get the research data, after we search via keywords and select the explosion criteria we reach 345 (study see table1), then we used Microsoft Excel to clean our data set, after that we used R Programming Studio software and VOSviewer software to get our results

The selected manuscripts that met the inclusion criteria were exported in CSV format and converted into VOSviewer software and an R Package data frame using the Open-Source R Package BIBLIOSHINNY to achieve precise findings.

Using the dimensionality-reduction approach, the quantity of data in the data set that was unrelated to the research was removed. Through extensive network mapping of those filtered data, the V.O.S. viewer and Biblioshiny from the R package assisted with data visualization, parameter filtering, and the construction of the data's social structures.

To reach our objectives we apply Main information, authors, document, topic trends, cluster affiliation, and journal analysis via using R Programming Package & VOSviewer soft wares.

2 we illustrate the annual production for Real-Time Surveillance Video Analytics, as we can observe from table 3 the first articles published in this field start in 2012, but the real production started in 2017 and stile increase till 2023, and we demonstrate the average citation per years, as we can see the average citation start from 2012 with 2 citations, while from 2014 till 2016 we have the largest citation quantity with 20 citations per year.

The most effective resources in Real-Time Surveillance Video Analytics, as we can see IEEE INTERNET OF THINGS JOURNAL, ACM INTERNATIONAL CONFERENCE PROCEEDING SERIES, IEEE ACCESS, and LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS) have the big influence on this field. In addition, we demonstrate the authors' production for every year from 2015 to 2023, as we can observe in table 7 CALYAM P have a large amount of citation from 2017 tile 2023, based on this analysis we can say CALYAM P is the best author during last five years.

The study illustrate the keywords co-occurrence analysis which have four basic nodes and every node represents a different color, each node of the network represents a keyword, and the basis nods are edge computing in red color, video analysis in purple color, internet of things in yellow color, and cloud computing in green color. Every node indicates the occurrence of the keyword, in the video analysis field, as we can see edge computing shows high co-occurrence with the internet of things, deep learning, video analysis, and public safety. In addition, there is a significant relationship between video analysis, deep learning, cloud coupling, and resource allocation. While the is less link between real-time video analysis, image edge detection, visual analytics, and object tracking and the study demonstrate the link between the country, The link among the nodes appears as the relationship between authors, so the thickness of the link signals the occurrence of citations between the authors, consequently, the thicker line represents the strong relationship among the authors, while the thinner line represents the weak relationship between the authors, as we can see there is a high link between USA with Canada, UK, China, France, and Ireland. Although, there is an insignificant relationship between South Korea, Australia, Ireland, Taiwan Hong Cong, and Canada.

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Author contributions

Sandhya Rani Nallola: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Software, Validation., Field study **Prof. Vadivel Ayyasamy:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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