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DATA ANALYTICS AND MACHINE LEARNING

Deepfakes: evolution and trends

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Abstract

This study conducts research on deepfakes technology evolution and trends based on a bibliometric analysis of the articles published on this topic along with six research questions: What are the main research areas of the articles in deepfakes? What are the main current topics in deepfakes research and how are they related? Which are the trends in deepfakes research? How do topics in deepfakes research change over time? Who is researching deepfakes? Who is funding deepfakes research? We have found a total of 331 research articles about deepfakes in an analysis carried out on the Web of Science and Scopus databases. This data serves to provide a complete overview of deepfakes. Main insights include: different areas in which deepfakes research is being performed; which areas are the emerging ones, those that are considered basic, and those that currently have the most potential for development; most studied topics on deepfakes research, including the different artificial intelligence methods applied; emerging and niche topics; relationships among the most prominent researchers; the countries where deepfakes research is performed; main funding institutions. This paper identifies the current trends and opportunities in deepfakes research for practitioners and researchers who want to get into this topic.

Keywords Deepfakes · Artificial intelligence · Deep learning · Bibliometrics

1 Introduction

Deepfake technology can be used to forge synthetic media that people cannot differentiate from true ones. It is a recent research area in which researchers in academia and industry have contributed deepfake databases, and synthesis and detection algorithms, which has made the deepfake popularity grow. Deepfakes are the product of artificial intelligence (AI) applications that merge, combine, replace, and superimpose images and video clips to create fake videos that appear authentic (Maras and Alexandrou 2019). Deepfakes use recent advances in deep neural networks to create hyper-realistic synthetic media. When deepfake technology is used on videos or images, the face of a person can be swapped with another face leaving little trace of manipulation (Chawla 2019). The emergence of deep learning has made previously existing fake face detection strategies vulnerable (Cho and Jeong 2017).

The availability of deepfake databases and synthesis and detection algorithms have made it possible for the community and even amateurish users to perform realistic deepfakes, which in turn has made the amount of popularity deepfake videos in the wild grow immensely (Pu et al. 2021a). Coupled with the reach and speed of social media, convincing deepfakes can quickly reach millions of people and have negative impacts on our society (Westerlund 2019).

The growth in deepfakes research has also been reflected in the amount of related scientific literature. Apart from technological aspects related to deepfake creation and detection, ethical, social, and legal aspects have also been carefully analyzed. There are already some reviews in specific fields, such as Creation and detection of deepfakes (Mirsky and Lee 2021), Law (da Silva 2021), Forensics (Amerini et al. 2021a), and Social impact (Hancock and Bailenson 2021a), to name a few. Still, none of them contemplates the full spectrum of research areas in deepfakes, which we believe can be very useful for researchers who wish to work on this

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research topic. Despite its novelty, deepfakes research is a fast-growing research area, in which the research topics and their relationship is continuously changing over time and new trends appear. The different areas in which deepfakes research is performed indicate there are researchers with a wide variety of backgrounds. Apart from current trends, analyzing the funding opportunities is interesting to help focus the research effort.

The objective of this work is to get an overview of the current trends and evolution of deepfakes research, as well as to analyze the fields in which it is being applied. To this aim, all the empirical evidence that fits pre-specified eligibility criteria to answer the following six specific research questions was collated in Scopus and Web of Science databases: What are the main research areas of the articles in deepfakes? What are the main current topics in deepfakes research and how are they related? Which are the trends in deepfakes research? How do topics in deepfakes research change over time? Who is researching deepfakes? Who is funding deepfakes research? It has been decided which disciplines are developing, which are consolidating, and which are promising. The most studied areas of deep learning research, including the various artificial intelligence techniques used, have also been examined, along with emerging and niche topics. Relationships between the most well-known scientists, the nations where deepfakes research is conducted, and the major funding organizations have also been established. The prospects and trends in deepfakes research are identified in this article for practitioners and scholars who are interested in the subject.

The remainder of this paper is structured as follows. The next section presents the methods used to obtain the sample of articles to study that determine the focus, the specific research questions we seek to answer, and the software used to automate part of the process. In the results section, we expose the findings of specified research questions. After providing some reflections on the discussion, conclusions are drawn.

2 Methods

A systematic review attempts to collate all the empirical evidence that fits pre-specified eligibility criteria to answer a specific research question (Higgins et al. 2019). Therefore, the authors have ensured that the review addresses relevant questions to those who are expected to use and act upon its conclusions. More specifically, the research questions addressed by this review paper are:

- RQ1: What are the main research areas of the articles in deepfakes?
- RQ2: What are the main current topics in deepfakes research and how are they related?
- RQ3: Which are the trends in deepfakes research?
- RQ4: How do topics in deepfakes research change over time?
- RQ5: Who is researching deepfakes?
- RQ6: Who is funding deepfakes research?

Table 1 Records retrieved from Scopus and Web of Science in July and October 2021, between parentheses those in English

	Results (in English)		
	July 2021	October 2021	Growth
Scopus	242 (229)	331 (311)	89 (82)
Web of Science	8 (6)	12 (10)	4 (4)

Once the research questions were established, the starting point was a search carried out in Scopus in July 2021 and another in October of the same year. The specific query used in the case of Scopus was:

```
ALL (
  ( deepfake deep-fake "deep fake" ) AND
  ( ( action unit  OR  facial action unit
     coding system  OR facs ) OR ( video
     OR  clip  OR  image  OR  photogram )
  ) )
```

The same procedure was followed in Web of Science (WoS) also in July and October. The query in the case of WoS was:

```
TS=(
  ( deepfake deep-fake "deep fake" )
AND  ((Action Unit OR Facial Action
      Unit Coding System OR FACS) OR
(video OR clip OR image OR photogram))
```

As summarized in Table 1, the Scopus query retrieved a total of 242 records (229 in English) in July and 331 (311 in English) in October. The range of years for the retrieved records was from 2018 to 2021. There were no results before 2018 from any of the databases. In the case of Web of Science, the results were 8 in July (6 in English) and 12 in October (10 in English).

The first objective of these queries was to check if the same articles were being published in both databases and to estimate the rate of growth of the number of publications from the change between the July and October requests. Given the small number of results from Web of Science, and that just one of them is not present in the Scopus results, the detailed analysis focuses on the October results in English, i.e., 311 records from Scopus, from now on the SDO21 (Scopus Database October 2021) dataset. The dataset records are listed in Appendix A, divided into clusters based on their keywords, and available for download online.[1] It is also important to note the importance that conference publications have concerning deepfakes research as they are not included in the Web of Science. One hundred and seventy-nine of the records from Scopus are conference papers.

Given the size of the SDO21 dataset, the review has been automated using the Bibliometrix (Aria and Cuccurullo 2017) package for R, including the Biblioshiny application, as detailed in Sect. 3. Regarding transparent reporting of systematic review and meta-analysis, a PRISMA Flow Diagram [2] has not been considered necessary because the process has been simple. All the records retrieved have been considered, with the only exception of articles not in English, to facilitate the automated analysis using Bibliometrix. In any case, as observed in Table 1, the number of records that are not in English just represents between 5% and 6% of the results, in July and October, respectively.

3 Results

3.1 Main topics in deepfakes research

Regarding the first two research questions,RQ1: What are the main research areas of the articles in deepfakes? and RQ2: What are the main current topics in deepfakes research and how are they related?, our first exploration considers just the review papers, the focus of which is mainly placed on ethical and legal aspects as detailed next:

- Forensics (Amerini et al. 2021a; Castillo Camacho and Wang 2021a)
- Pornography (Karasavva and Noorbhai 2021a)
- Law (O'Donnell 2021; da Silva 2021; Aboueldahab and Freixo 2021a; Colon 2020a; Meskys et al. 2020a; Farish 2020a; Perot and Mostert 2020a)
- Theater (Fletcher 2018a)
- Social impact (Hancock and Bailenson 2021a)
- Social spam (Rao et al. 2021)
- Creation and detection of deepfakes (Mirsky and Lee 2021).

If we broaden to the whole set of 311 papers and just analyze the research areas they belong to, Computer Science is the most represented with 40.8% of the records related to this area. It is followed by Engineering (19,5%) and Social Sciences (9,4%), as shown in Fig. 1. It is important to note that papers might belong to more than one area, as defined by the corresponding literature database for each journal and year. We consider all areas when calculating these percentages as a way to recognize the interdisciplinary nature of deepfakes, with scientific journals aiming to promote interdisciplinary research and facilitate collaboration among researchers with diverse expertise.

To get deeper into the specific topics deepfakes research is dealing with, a knowledge discovery approach has been applied to identify the underlying conceptual structure. The keywords associated with each record in the SDO21 dataset have been analyzed with the Bibliometrix R package. The conceptual structure represents the relationship among the records' keywords. Keywords that appear together in a paper corresponding to a record are connected in the resulting co-keywords network. Keywords will be close in this network if a large proportion of papers have them together. Otherwise, they will be apart.

The process to create this co-keywords network that highlights the main research topics is first to create a co-occurrence symmetric matrix. As shown in Fig. 2, the elements in the diagonal k_{ii} correspond to the total amount of occurrences of each keyword in the whole SDO21 dataset. On the other hand, the element outside of the diagonal, k_{ij}, corresponds to how many times the keyword i and keyword j appear together in the same paper.

The co-keywords matrix is then used to generate the keywords network that highlights the research topics structure in deepfakes research. The network is an undirected graph where the nodes correspond to keywords and whose size depends on the keyword frequency, thus generated from the matrix's diagonal.

Then, two graph nodes are connected if the matrix cell for the corresponding keywords is greater than 0, and thus both keywords share at least one paper. The edges are weighted with the value of that cell, i.e., the number of papers where both keywords appear together as captured in the non-diagonal cells. Edges' weight is interpreted as a measure of the strength between two keywords, the higher they appear the closer they are on the graph. Based on this interpretation of the matrix, the graph can be rendered as shown in Fig. 3 and highlights the main research topics corresponding to the most frequent keywords. This technique processes keywords as text strings and thus does not include any kind of semantic similarity measure. It focuses on the keywords associated with each publication.

Co-occurrence networks use various measures to identify crucial nodes or vertices within the network. Among these measures, Betweenness (Table 2), Closeness (Table 3), and PageRank (Table 4) are used to provide notable insights. When considering the top 5 keywords for each metric, a sum of 8 unique keywords is obtained. This is consistent as each measure is capturing a different aspect of the network of keyword co-occurrences. Betweenness quantifies how often a node falls on the shortest paths between other nodes in

[1] Replication data, https://doi.org/10.34810/data750.

[2] http://prisma-statement.org.

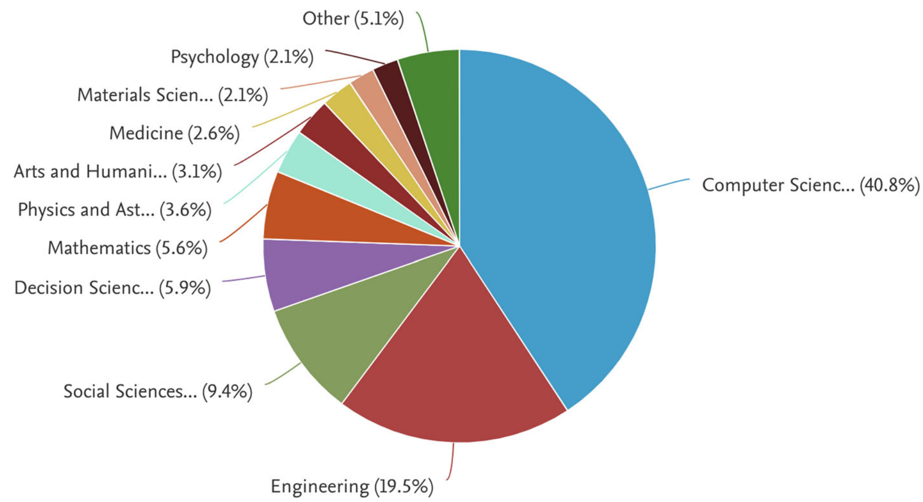


Fig. 1 Main research areas for the papers included in the SDO21 dataset (311 records retrieved from Scopus on October 2021)

$$\begin{bmatrix} k_{11} & k_{12} & k_{13} & \dots & k_{1n\text{-}1} & k_{1n} \\ k_{21} & k_{22} & k_{23} & \dots & k_{2n\text{-}1} & k_{2n} \\ k_{31} & k_{32} & k_{33} & \dots & k_{3n\text{-}1} & k_{3n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ k_{n\text{-}11} & k_{n\text{-}12} & k_{n\text{-}13} & \dots & k_{n\text{-}1n\text{-}1} & k_{n\text{-}1n} \\ k_{n1} & k_{n2} & k_{n3} & \dots & k_{nn\text{-}1} & k_{nn} \end{bmatrix}$$

Fig. 2 Co-keyword matrix used to generate the network highlighting the research topics in deepfakes research shown in Fig. 3

the network. Nodes with high Betweenness are critical since they connect different parts of the network, playing a vital role in the flow of information or resources between distinct groups of nodes. Closeness measures how closely connected a node is to all other nodes in the network. Nodes with high Closeness are significant since they have rapid access to a vast amount of information or resources and can disseminate them quickly throughout the network. PageRank assesses a node's importance based on the number and quality of incoming links it has. Nodes with high PageRank are crucial since they are highly connected to other important nodes in the network. In identifying key intermediaries or brokers in the network, Betweenness is the most critical measure. If the aim is to identify nodes that can quickly disseminate information throughout the network, Closeness is the most critical measure. Finally, to identify nodes that shape the network's overall behavior, PageRank is the most important measure. It is often useful to calculate all three measures to gain a comprehensive understanding of the network's structure and dynamics.

This representation makes it easier to visualize how the main research topics are organized in deepfakes research. Just the most representative topics, corresponding to the most used keywords, are shown. And they are more prominent the more present they are in the SDO21 dataset. Highly related topics, because they are covered jointly in many papers, are shown closer. This makes it also possible to apply a clustering algorithm that helps identify the main research topics and

Table 2 Top 5 keywords by co-occurrence (Betweenness)

Node	Cluster	Betweenness
Deep learning	5	334.138
Convolutional neural networks	2	172.340
Face recognition	3	123.595
Detection methods	5	85.786
Computer vision	3	68.919

Table 3 Top 5 keywords by co-occurrence (Closeness)

Node	Cluster	Closeness
Deep learning	5	0.0164
Convolutional neural networks	2	0.015
Detection methods	5	0.0144
Face recognition	3	0.014
Digital forensics	2	0.013

Table 4 Top 5 keywords by co-occurrence (PageRank)

Node	Cluster	PageRank
Deep learning	5	0.105
Convolutional neural networks	2	0.066
Detection methods	5	0.059
Face recognition	3	0.054
Adversarial networks	2	0.040

the central keywords giving the name to the corresponding topics:

- Red: deep learning, adversarial networks, learning systems, etc.
- Blue: face recognition, detection methods, forgery detections, etc.

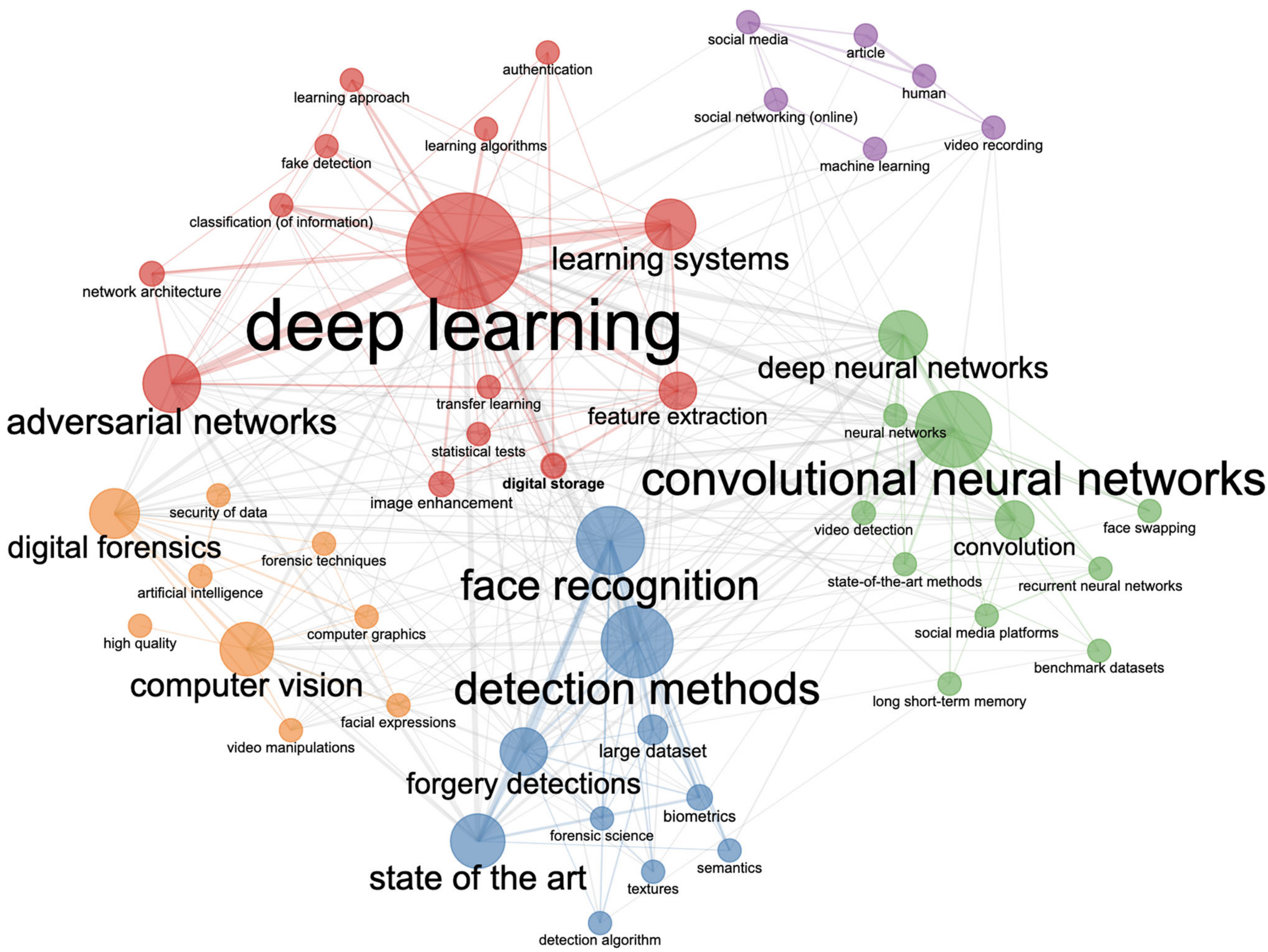


Fig. 3 Co-keywords graph representing the main research topics in deepfakes research

- Green: convolutional neural networks, deep neural networks, etc.
- Orange: computer vision, digital forensics, etc.
- Purple: social media, video recording, social networking, etc.

3.2 Trends and evolution of deepfakes research

In this section, we address the third and fourth research questions, RQ3: Which are the trends in deepfakes research? and RQ4: How do topics in deepfakes research change over time?. Despite the short time interval under study, the SDO21 dataset includes records from 2018 to 2021, it is possible to observe the evolution of the main research topics and identify their trends.

First of all, after applying a clustering algorithm to the keywords as detailed in the previous section, we can do more than just highlight the main topics of the deepfakes research domain. Each topic can be represented on a plot called Thematic Map (Cobo et al. 2011) as shown in Fig. 4.

This kind of plot classifies the cluster of keywords from the co-keyword network obtained in the previous section according to Callon's centrality and density measures (Callon et al. 1991):

- *Centrality*: measures the strength of the links to other topics, considering those from keywords included in a cluster to keywords in other clusters. Thus, it measures the importance of a topic in the context of the whole field of study.
- *Density*: is related to the strength of internal links among all keywords corresponding to the same topic cluster. It is interpreted as a measure of the topic's development degree.

Centrality and Density define the two axes of the Thematic Map and are used to divide it into four regions. The topics in these regions are associated with the following trends:

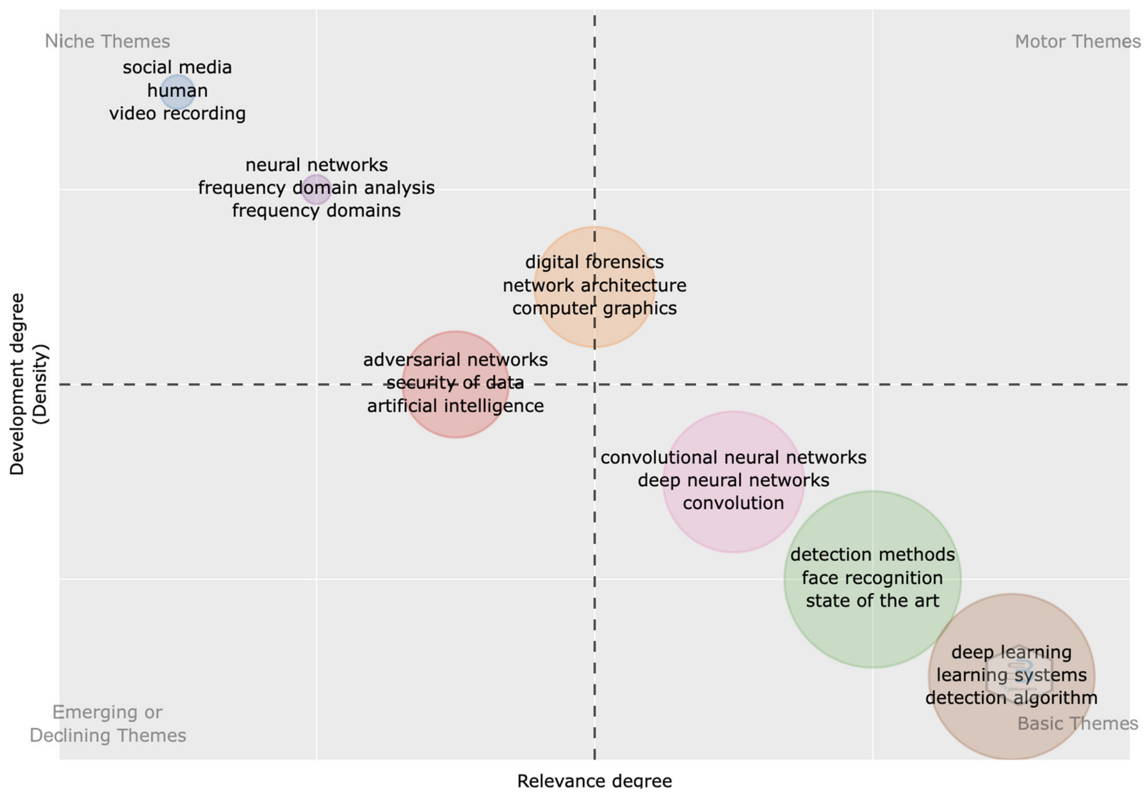


Fig. 4 Thematic Map the topic trends in deepfakes research. From top-left to bottom-right: Niche, Motor, Emerging, and Basic topics

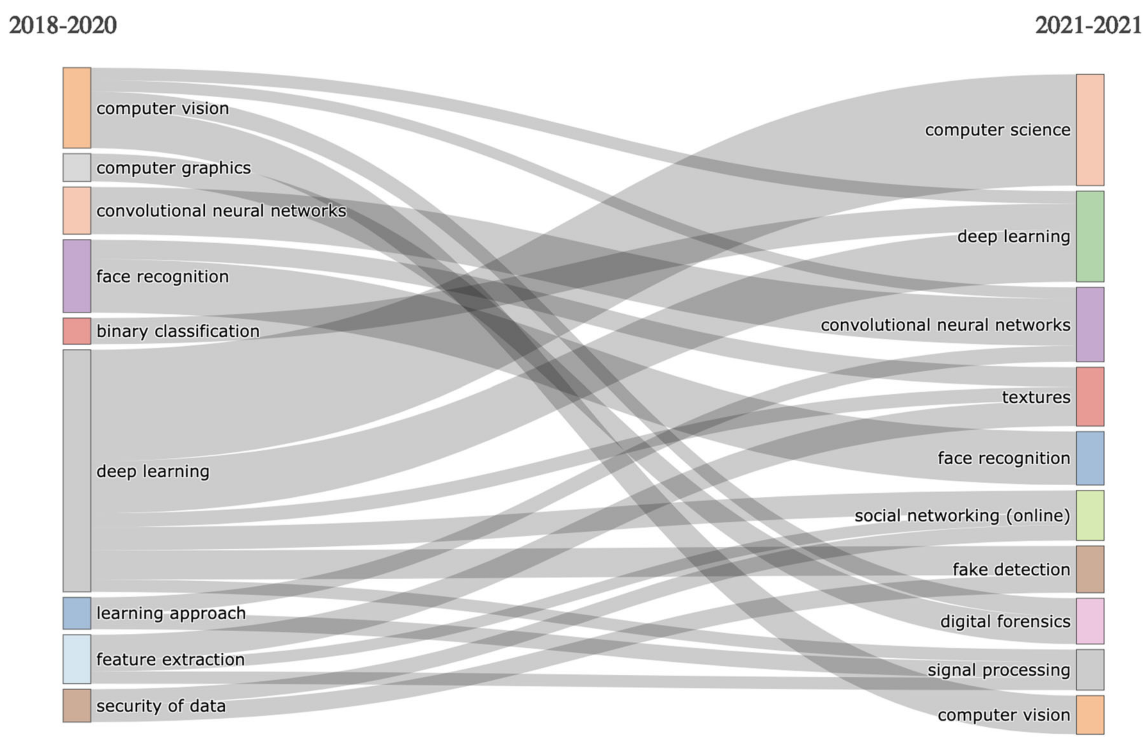


Fig. 5 This is the keywords plus graph. The colors represent the different clusters: deep learning (red), convolutional neural networks (green), computer vision (orange), and detection methods (blue)

- *Niche Topics (upper-left quadrant)*: well-developed internal ties but unimportant external ties and so, they have a marginal role in the development of the research field under study. Non-central but dense.
- *Motor Topics (upper-right quadrant)*: these topics are both well-developed and important in the context of the analyzed records. High centrality and density.
- *Emerging or Declining Topics (lower-left quadrant)*: they are both weakly developed and marginal, with low centrality and density.
- *Basic Topics (lower-right quadrant)*: they are important for a research field but are not developed, i.e., they show high centrality but low density.

The Motor and Basic topics are considered those that favor the development and consolidation of a research field due to their density and/or centrality. For the particular case of deepfakes research captured by the SDO21 dataset, there is a lack of clear Motor Topics. Most of them are Basic Topics related to the core of technologies used for deepfakes development, as is the case of convolutional neural networks or deep neural networks. This is also the case with detection methods such as facial recognition.

The only topics that are partially classified as Motor Topics, and thus are computer graphics, network architecture, and digital forensics. This seems related to the fact that, as noted at the beginning of Section 3.1, there are two reviews on the particular topic of forensics in the last four years.

On the other hand, the topics partially related to Emerging Topics (declining seems unfeasible given the youth of the discipline and the short time range) are those associated with artificial intelligence, data security, and adversarial networks. Finally, the more mature topics, though apart from the main efforts in this research domain, are those that have to do with the analysis in time and frequency to achieve better returns such as video recording or social networks.

It is important to note that what is being classified into these different trends are the keywords associated with the papers. Thus, quite related topics that might be even equivalent in some contexts, like "deep neural networks" and "neural networks," might be classified in different quadrants based on their use in the analyzed literature. The approach is thus completely agnostic regarding the interpretation of these keywords because they are highly contextual, like in the case of neural networks methods and applications (Samek et al. 2021).

In addition to the static view provided by the Thematic Map in Fig. 4, it is also possible to get an idea of the underlying dynamics using the Thematic Evolution diagram shown in Fig. 5. Thematic Maps for different periods are computed to identify topics' evolution over time. Topics at a particular period are then connected with those in the following one to create a stream of topics' evolution. Linking among topics is based on the percentage of keywords shared between the identified topics at each period. This way, it is possible to observe how initial topics might remain partially and split into other topics that then include the corresponding keywords.

For the SDO21 dataset, just two time periods have been defined given the short period, 2018–2020 and 2021. On the left of Fig. 5, there are the topics for the 2018–2020 period, including computer vision or computer graphics among others. On the right side, are those for 2021. The evolution of the topics is illustrated through the links connecting them, which are weighted based on the number of keywords shared by the topics in different periods.

For instance, the computer vision topic has split into many different ones in 2021, partially remaining as the same topic but less relevant because many of the associated keywords are now tied to other topics like deep learning, convolutional neural networks, or digital forensics. On the other hand, topics like computer graphics have disappeared and now the associated keywords are contributing to the digital forensics one, which has emerged from keywords from this topic combined with some from computer vision. Overall, Fig. 5 highlights the topics getting traction in deepfakes research and how they are consolidating from the topics that attracted the most attention just some years ago.

3.3 Deepfake technologies usage and funding

Regarding the last research questions, RQ5: Who is researching deepfakes? and RQ6: Who is funding deepfakes research?, they are addressed by analyzing the intellectual and social structures of the SDO21 dataset. First of all, and as can be observed in Table 5, the most relevant papers come from conferences, concretely from IEEE conferences and workshops. Forensics, signal processing, law, and blockchain are among the topics dealt with by the most cited articles about deepfakes research in Scopus between 2018 and 2021.

Going beyond this superficial analysis, the whole community that has generated the papers in SDO21 should be taken into account. It is for this reason that we have also carried out an analysis of the social structure to highlight how authors or institutions related to others in this particular research field. First of all through a co-authorship network, which is displayed in Fig. 6.

Many of the most referenced authors in Table 5 can be also identified in the co-authorship network, which also focuses on the most prominent authors. These authors appear in little clusters, like Amerini or Agarwal and their corresponding co-authors. This highlights that even highly cited authors' work collaborates in relatively closed circles and the overall community is quite fragmented from this perspective.

If we switch from individual researchers to their institutions and countries, we can also unveil the underlying

Table 5 The first 10 most cited articles in SDO21 between 2018 and 2021

Title	Publisher	Citations	References
FaceForensics++: Learning to Detect Manipulated Facial Images	IEEE	302	Rossler et al. (2019)
Exposing Deep Fakes Using Inconsistent Head Poses	IEEE	165	Yang et al. (2019a)
Exploiting Visual Artifacts to Expose Deepfakes and Face Manipulations	IEEE	136	Matern et al. (2019a)
Protecting World Leaders Against Deep Fakes	IEEE	105	Agarwal et al. (2019a)
Combating Deepfake Videos Using Blockchain and Smart Contracts	IEEE	80	Hasan and Salah (2019a)
Deep Fakes: A Looming Challenge for Privacy	California Law	72	Chesney and Citron (2018)
Celeb-DF: A Large-Scale Challenging Dataset for DeepFake Forensics	IEEE	64	Li et al. (2020d)
Detecting and Simulating Artifacts in GAN Fake Images	IEEE	49	Zhang et al. (2019b)
Media Forensics and DeepFakes: An Overview	IEEE	47	Verdoliva (2020)
Deepfake Video Detection through Optical Flow Based CNN	IEEE	44	Amerini et al. (2019a)

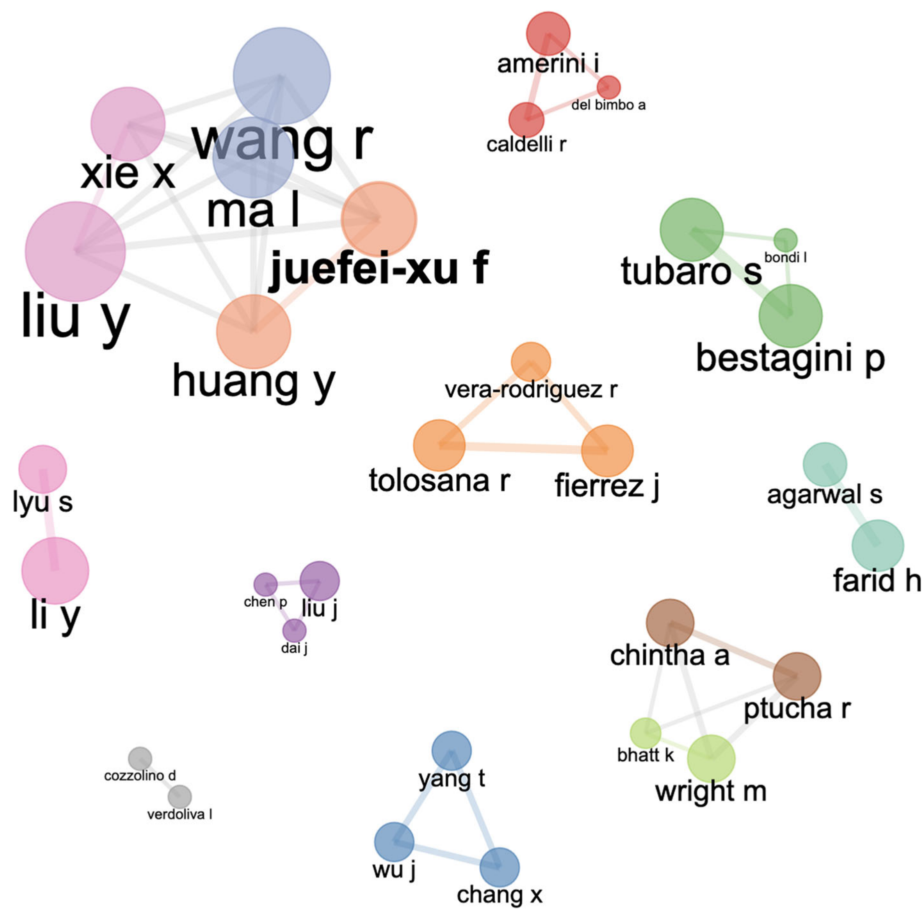


Fig. 6 Co-authorship network showing some of the more prominent authors in SDO21

social structures at these levels. Looking at the corresponding author countries, shown in Fig. 7, we can observe the great leadership that researchers from China have in this particular research area.

This is even more evident when we realize that, despite it might seem that part of this leadership comes from collaborations with other countries because it is the country with the highest amount of inter-country collaborations, these collaborations are really with Chinese researchers based in other countries. This is illustrated in Fig. 8, which shows the connection between researchers and countries, and then from countries to research topics. Therefore, although inter-country collaboration is indeed very high in China, it is because these researchers work in other countries, in most cases in the USA as shown in Fig. 8.

Finally, focusing on RQ6: Who is funding deepfakes research?, the main research funding organization of the reviewed publications is the National Natural Science (Foun-

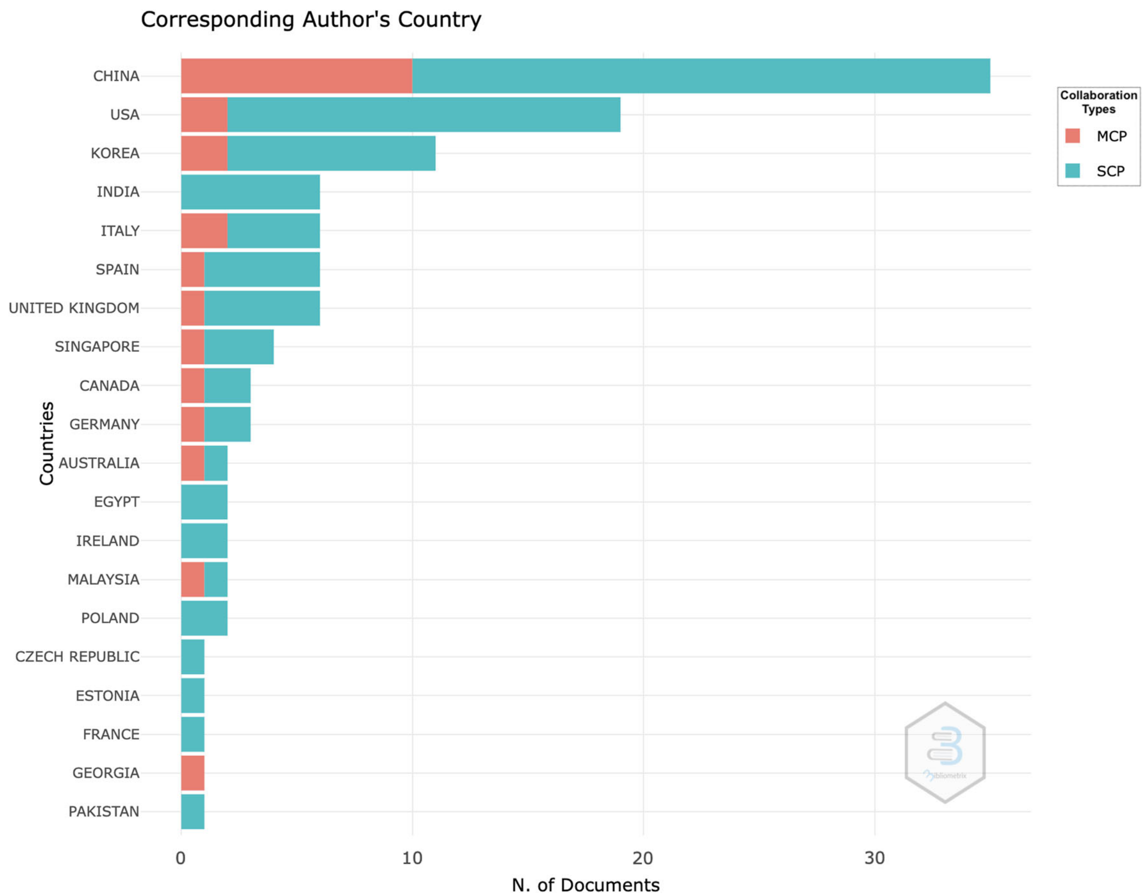


Fig. 7 Corresponding author's countries, including intra-country (SCP) and inter-country (MCP) collaborations in SDO21

dation of China) with 30 publications, followed by the Defense Advanced Research Projects Agency (US DARPA) with 22, and the National Key Research and Development Program of China with 13. Then, with 12 publications, we find the US Air Force Research Laboratory and the US National Science Foundation. A complete table with the top 10 funding organizations is shown in Table 6. Therefore, China is leading the investigation as a country, mostly from institutions related to the military and defense sectors. And as shown in Fig. 9, which displays the collaborations among institutions, these collaborations are kept at the national level.

4 Discussion

This paper employs metadata analysis to investigate the trends and tendencies related to deepfake research. It is important to note that our objective was not to conduct a literature review, but to analyze its metadata. However, it may be valuable to include this section in the paper that provides further insights into the representative results of the included publications.

Deepfakes is a field of research that has gained significant attention in recent years due to its potential implications in manipulating digital media. Following the content found in the lower-right quadrant of Fig. 4, which contains "topics that are important for the research field but are not yet fully developed" learning systems, detection methods, and algorithms are the key and future directions in the topic. One of the most common approaches used in Deepfakes is generative adversarial networks (GANs) (Hu et al. 2021). These techniques consist of two neural networks, one that generates fake data and another that evaluates the generated data authenticity. The results obtained using GANs have shown remarkable progress in generating highly realistic images and videos. Another popular method is the use of autoencoders (Singh et al. 2021), neural networks that are trained to reconstruct the input data. The encoded representation of the input is then used to generate new data. The results obtained using autoencoders have shown promise in generating high-quality Deepfakes.

In addition to GANs and autoencoders, there are other methods that have been used in Deepfakes, such as variational autoencoders (Zendran and Rusiecki 2021), deep belief networks (Iacobucci et al. 2021), and convolutional neural

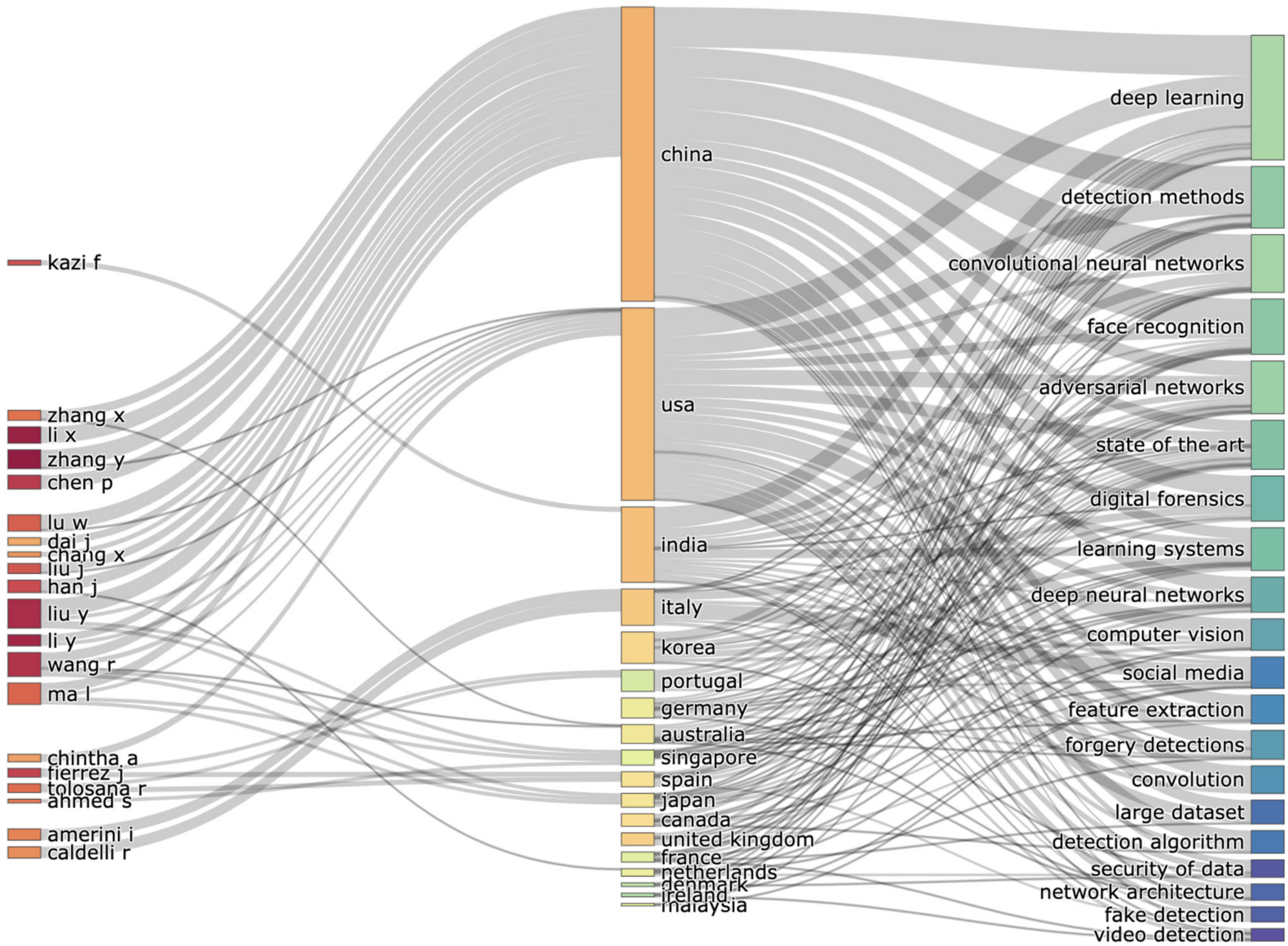
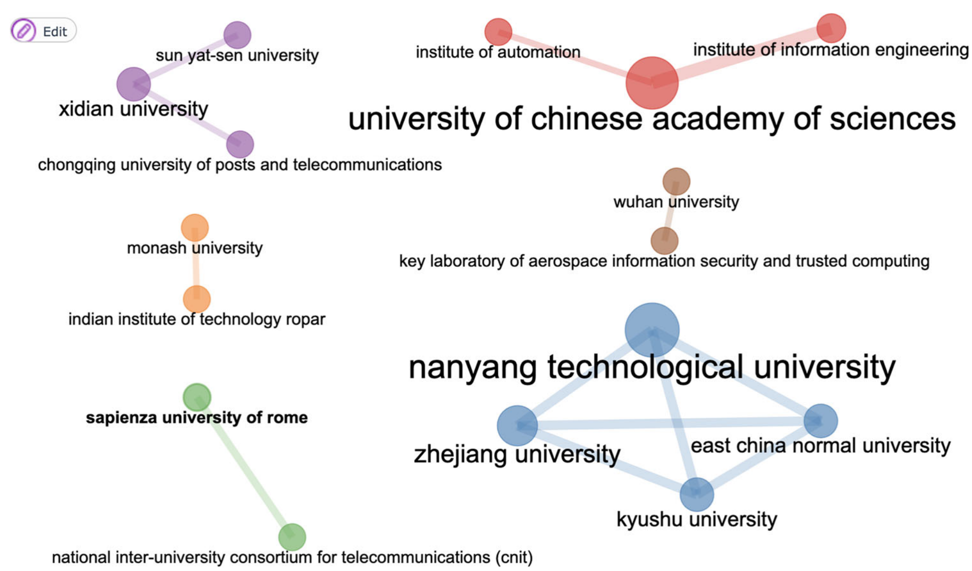


Fig. 8 Relationships among the most prominent researchers, the countries where they conduct research, and the main research topics per country

Fig. 9 Collaboration among institutions as derived from the records in the SDO21 dataset



networks (Agrawal and Sharma 2021). Each of these methods has shown varying degrees of success in generating Deepfakes. Of course, these methods are improving by applying not only new approaches but combining known techniques in a new way, as Zheng et al. (2018) proposes a novel two-stage training process for deep convolutional neural networks (CNNs) that improves their generalization ability by implicit regularization, particularly when the training data is limited.

Practical cross-area applications can be found in works like (Yao et al. 2021), where a method is proposed to automatically separate compound figures in biomedical research articles. It uses a deep learning model that is trained to separate the subfigures based on their visual features and is augmented with a "side loss" to ensure that the model also considers the context and layout of the subfigures. This article is a good example of how a single publication can show insights into distant topics from upper-left Fig. 4 (frequency domain analysis) and lower-right (detection methods) at the same time.

Despite the progress made in deepfakes, there are still limitations to the current state of the art. The primary challenges are the ability to generate realistic and high-quality deepfakes without significant artifacts (Matern et al. 2019b) and paradoxically, the ability to detect and prevent the spread of deepfakes in the public domain (Rossler et al. 2019).

Finally, regarding funding, the top five funding institutions are either government agencies (NSFC, DARPA, AFRL, and NSF) or state-sponsored programs (NKRDPC and USNCF) that prioritize funding for research projects that are strategically important to their respective countries (see Table 6). As these projects may include those with military applications or those that promote the development of key industries, it is reasonable to infer that these strategic priorities may account for the low inter-country collaboration ratio (MCP) presented in Fig. 7. This could be because research with strategic importance often challenges collaboration due to national security concerns, funding restrictions (in some cases, funds may be restricted for international collaborations), and intellectual property issues.

5 Conclusions

It has been found that growth since 2018 has skyrocketed regarding research publications in the area of deepfakes. The queries for Web of Science and Scopus did not retrieve any results before 2018 but accumulated 311 results, after less than four years, in 2021. The specific findings for each of the research questions are discussed in the next paragraphs.

RQ1: What are the main research areas of the articles in deepfakes? Deepfakes research includes many different research areas. Our analysis identified 10 different areas with at least 2% of the articles about the topic. All 10 combined represent roughly 95% of the papers. However, there is a big imbalance as just 3 of them accumulate almost 70% of the results. Computer Science is the most represented with 40.8%, followed by Engineering (19,5%). Thus, these technological research areas are those with the biggest percentage of articles. The third area is Social Sciences (9,4%), so deepfakes research is also noticeable in social sciences-related topics.

RQ2: What are the main current topics in deepfakes research and how are they related? Regarding the most studied topics, a knowledge discovery approach has been applied to identify the underlying conceptual structure starting from the keywords associated with the analyzed articles. Using a clustering algorithm, five main sets of topics have been identified, being the most representative topics in each cluster: deep learning, face recognition, convolutional neural networks, computer vision, and social media. Other relevant topics in each cluster are presented in Fig. 3. As can be observed, overall, deep learning stands out. And more specifically, adversarial and convolutional neural networks. It is also relevant to the research on forgery detection and the literature related to face recognition.

RQ3: Which are the trends in deepfakes research? The main topics identified using clustering have been analyzed using a Thematic Map, shown in Fig. 4. This kind of plot classifies the clusters of keywords obtained in the previous section according to Callon's centrality and density measures (Callon et al. 1991). Based on these measures, we can identify:

- *Niche Topics*: well-developed but with a marginal role in the development of the research field, like Social Media related to Video Recording or Neural Networks in the context of Frequency Domain Analysis.
- *Emerging or Declining Topics*: these are weakly developed and still marginal topics. Given the youth of the deepfakes discipline, they should be mainly emerging topics. Though the analysis does not identify clear emerging topics, research related to adversarial networks in the context of security might be considered an emerging area with potential relevance in the future.
- *Motor Topics*: these are both well-developed and important in the context of deepfakes. As previously stated, the youth of the discipline causes a lack of clear candidates. Just topics related to computer graphics, network architecture, and digital forensics might be classified as Motor.
- *Basic Topics*: these are the topics on which research should be focused. They are important for deepfake research but have not been developed yet. Here, we can find the bulk of the research. The most promising topics are convolutional deep neural networks and detection methods based on face recognition or deep learning.

Table 6 Top 10 Research Funding Organizations

Institution	Funded Projects
National Natural Science (Foundation of China)	30
Defense Advanced Research Projects Agency, DARPA	22
National Key Research and Development Program of China	13
Air Force Research Laboratory, AFRL	12
US National Science Foundation	12
Google	5
Nvidia	4
Ministry of Science and ICT, South Korea, MSIT	4
Ministero dell'Istruzione, dell'Università e della Ricerca	4
National Research Foundation of Korea, NRF	4

RQ4: How do topics in deepfakes research change over time? In addition to the dynamics of deepfakes research captured by the previous trends analysis, it is also possible to visualize the underlying dynamics using a Thematic Evolution chart, as shown in Fig. 5. We use Thematic Maps for different periods, which are then connected with those in the following one to create a stream of topics' evolution based on the percentage of keywords shared between the identified topics at each period. An insight that can be derived from this diagram is the diversification of the research around deep learning, which remains one of the main topics but with clear applications to texture analysis, fake detection, or online social networking. The same can be said about computer vision, which gets out of the main focus even more than deep learning. On the contrary, from a technical perspective, convolutional neural networks are getting more attention from recent research compared to the beginning of the analyzed period.

RQ5: Who is researching deepfakes? and RQ6: Who is funding deepfakes research? It is China as a country the one that directs the investigations, being the one that contributes the most in all regards, including funding through the Natural Science Foundation of China and NKRDPC. Researchers are mainly from this country, though many of them perform their research in the USA. On the other hand, the collaboration communities in this research area are still small and fragmented as observed when studying the co-authorship network. Usually, they are formed by just 2 or 3 authors, except for the most prolific Chinese researchers that are organized in a community of 6 authors. The same happens at the country level, most collaborations are among institutions of the same country. Additionally, though authors might be based on centers in different countries, we do not observe inter-country collaborations.

In addition to the conclusions regarding the different research questions, we have identified some missing research topics that we think should already be in the literature, such as research on the repercussions of deepfakes on marketing or online negotiation processes. These kinds of risks have been tangentially addressed in the context of studies about identity usurpation, which have been the topic of some law journals. In any case, we believe that considering the emerging risks of deepfakes in connection with tasks like online meetings is crucial.

As a limitation of this work, the number of articles found on deepfakes research made it impossible to perform a systematic literature review or meta-analysis on the whole area of deepfakes research. On the other hand, this type of study can be carried out by focusing on more specific aspects of the area identified by this work, such as the different artificial intelligence techniques used to synthesize or analyze deepfakes.

To conclude, the research articles retrieved about deepfakes serve to provide a complete overview of deepfakes. The main insights of this work include the various areas in which deepfakes research is being conducted, focusing on which areas are emerging, those that are considered basic, and those that currently have the greatest potential for development. The most studied topics in deepfakes research, including the various artificial intelligence methods employed, are analyzed together with emerging and niche topics, to provide insight into the current trends.

The relationships among the most prominent researchers, together with the countries in which deepfakes research is conducted and the main funding sources, complete the outlook regarding the people who carry out research in that area and the options for collaboration and obtaining existing funds.

Overall, this article discusses current trends and opportunities in deepfakes research for practitioners and researchers interested in this field. Future research directions emerging from the review point in the direction of the identified "Basic Topics": convolutional deep neural networks and detection methods based on face recognition or deep learning.

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Author Contributions Rosa Gil and Juan-Miguel López-Gil were involved in conceptualization and methodology; Jordi Virgili-Gomà and Roberto García helped in data curation; Roberto García contributed to funding acquisition; Jordi Virgili-Gomà was involved in validation; Rosa Gil helped in visualization; Rosa Gil, Juan-Miguel López-Gil, and Roberto García contributed to writing—original draft; Jordi Virgili-Gomà, Rosa Gil, Juan-Miguel López-Gil, and Roberto García helped in writing—review & editing.

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Data Availability The datasets generated and analyzed during the current study are available online at https://drive.google.com/file/d/1Attj4yMnsYJB1rx9kYIdVVoQeMhqhW7k/view and are in the process of being published in the CORA-RDR repository, https://dataverse.csuc.cat.

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

Appendix A References in SDO21 Dataset

The following table lists all references in the SDO21 dataset of records retrieved from Scopus as detailed in Sect. 1. They are divided into 4 clusters centered on the keywords associated with each of them.

Cluster	References
deep learning 27.2% detection methods 18.5% face recognition 18.5%	Li et al. (2020c), Dang et al. (2020), Ciftci et al. (2020), Lyu (2020), Nguyen et al. (2021), Carlini and Farid (2020), Tursman et al. (2020), Kaur et al. (2020), Masi et al. (2020), Feng et al. (2020), Maksutov et al. (2020), Amerini et al. (2019b), Javed et al. (2021), Kuang et al. (2021), Patil et al. (2021), Megías et al. (2021), Patil and Chouragade (2021), Xu et al. (2021b), Jiang et al. (2021), Bonomi et al. (2021), Shang et al. (2021), Ling et al. (2021), Fung et al. (2021), England et al. (2021), Fazheng et al. (2021), Zhao et al. (2021b), Valenzuela et al. (2021), Xiang et al. (2021), Hosler et al. (2021), Caldelli et al. (2021), Pan et al. (2021), Khalil and Maged (2021), Demir and Ciftci (2021), Li and Lyu (2021), Whler and Zembaty (2021), Kohli and Gupta (2021), Lv (2021), Dondero (2021), Guo et al. (2021), Carter et al. (2021), Tu et al. (2021), Shelke and Kasana (2021), Pokroy and Egorov (2021), Tjon et al. (2021), Sun et al. (2021), Sankaranarayanan et al. (2021), Li et al. (2021a), Yang et al. (2021b), Kawa and Syga (2021), Gong et al. (2021), Hussain et al. (2021), Godulla et al. (2021), Tolosana et al. (2021), Jeong et al. (2021), Hernandez-Ortega et al. (2021), Zhang et al. (2021a), Deshmukh and Wankhade (2021), Caporusso (2021), Amerini and Caldelli (2020), Zhu et al. (2020a), Bonettini et al. (2020), Kukanov et al. (2020), Bondi et al. (2020), Nasar et al. (2020), Mittal et al. (2020a), Du et al. (2020a), El Rai et al. (2020), Ramadhani and Munir (2020), Gupta et al. (2020), Du et al. (2020b), Lewis et al. (2020), Chugh et al. (2020), Shah et al. (2020), Tarasiou and Zafeiriou (2020), Ross et al. (2020), Nguyen and Derakhshani (2020), Khodabakhsh and Loiselle (2020), Li et al. (2020e), Zotov et al. (2020), Wu et al. (2020a), Hongmeng et al. (2020), Chowdhury and Lubna (2020), Suratkar et al. (2020a), Hewage and Ekmekcioglu (2020), Zhao et al. (2020b), Younus and Hasan (2020a), Alattar et al. (2020), Li et al. (2020a), Peng et al. (2020), Ivanov et al. (2020), Zhao et al. (2020a), Cozzolino et al. (2019)

Cluster	References
deep learning 11.3% adversarial networks 7.5% artificial intelligence 6.6%	Kietzmann et al. (2020), Ahmed et al. (2021), Jung et al. (2020), Wang et al. (2020a), Mirsky and Lee (2021), Meskys et al. (2020a), Chesney and Citron (2019), Zhang et al. (2020), Fallis (2020), Maddocks (2020), Farish (2020a), Fletcher (2018a), Rao et al. (2021), Khormali and Yuan (2021), Lai and Patrick Rau (2021), Yu et al. (2021), Pavis (2021), Lees et al. (2021), de Seta (2021), Bode et al. (2021), Holliday (2021), Mihailova (2021), Bode (2021), Ayers (2021), Hayward and Maas (2021), Ahmed (2021c), Kim et al. (2021a), Sybrandt and Safro (2021), Diakopoulos and Johnson (2021), José and García-Ull (2021), Huber et al. (2021), Tahir and Batool (2021), Nygren et al. (2021), Fagni et al. (2021), Medoff and B.K. (2021), Pu et al. (2021b), Castillo Camacho and Wang (2021b), Mcglynn and Johnson (2021), D'Alessandra and Sutherland (2021), Freeman (2021), Karasavva and Noorbhai (2021a), Brooks (2021), Iacobucci et al. (2021), Hancock and Bailenson (2021a), Johnson (2021), Choraś et al. (2021), Tesfagergish et al. (2021), O'Donnell (2021), da Silva (2021), Thaw et al. (2021), Frick et al. (2021), Aboueldahab and Freixo (2021a), Hänska (2021), Zhang et al. (2021b), de Ruiter (2021), Ahmed (2021b), Murphy and Flynn (2021), Zhao et al. (2021a), Wahl-Jorgensen and Carlson (2021), Pavlíková et al. (2021), Dasilva et al. (2021), Vizoso et al. (2021), Johnson and Diakopoulos (2021), Chi et al. (2021), Kietzmann et al. (2021), Dobber et al. (2021), Kwok and Koh (2021), Kikerpill (2020), Perot and Mostert (2020a), Hasan and Salah (2019a), Aliman and Kester (2020), Xie et al. (2020), Pan et al. (2020), Kozyreva et al. (2020), Partadiredja et al. (2020), Tulk Jesso et al. (2020), Colon (2020a), Gosse and Burkell (2020), Lomnitz et al. (2020), Wang et al. (2020b), Katarya and Lal (2020), Kaye and Johnson (2020), Gandhi and Jain (2020), Chang et al. (2020), Šepec and Lango (2020), Hosier and Stamm (2020), Hartmann and Giles (2020), Gong et al. (2020), Jongman (2020), Pertsch et al. (2020), Shahar and Hel-Or (2020), Houde et al. (2020), Zhu et al. (2020b), Jeong (2020), Amelin and Channov (2020), Kang and Park (2020), Pashentsev (2020), Davis and Fors (2020), Hazan (2020), Bore (2020)

Cluster	References
deep learning 27.7% convolutional neural networks 23.1% detection methods 16.9%	Yang et al. (2019b), Jiang et al. (2020), Agarwal et al. (2019b), Agarwal et al. (2020a), Mittal et al. (2020b), Zi et al. (2020), Agarwal et al. (2020b), Chen et al. (2020), Montserrat et al. (2020), Ahmed (2021a), Marcon et al. (2021), Ajoy et al. (2021), Liang and Deng (2021), Ru et al. (2021), Tran et al. (2021), Ismail et al. (2021), Yavuzkilic et al. (2021), Fei et al. (2021), Yang et al. (2021a), Siegel et al. (2021), Agarwal and Farid (2021), Masood et al. (2021), Singh et al. (2021), Sanghvi et al. (2021), Xu et al. (2021a), Agrawal and Sharma (2021), Zendran and Rusiecki (2021), Trinh et al. (2021), Li et al. (2021b), Lu et al. (2021), Su et al. (2021), Luo et al. (2021), Biswas et al. (2021), Jiang et al. (2021), Korshunov and Marcel (2021), Chen and Tan (2021), Jin et al. (2021), Khalil et al. (2021), Gu et al. (2021), Yang et al. (2021c), Chintha et al. (2020a), Younus and Hasan (2020b), Korshunov and Marcel (2019), Suratkar et al. (2020b), Mitra et al. (2020), Liang et al. (2020), Burroughs et al. (2020), Huang et al. (2020a), Chintha et al. (2020b), Ki Chan et al. (2020), Zhu et al. (2020c), Yang et al. (2020), Wu et al. (2020b), Jafar et al. (2020), Şener (2020), Malolan et al. (2020), Fernandes and Jha (2020), Pantserev (2020a), Wang et al. (2020c), Zeng et al. (2020), Pantserev (2020b), Karandikar et al. (2020), Megahed and Han (2020), Albahar and Almalki (2019), Sohrawardi et al. (2019)
deep learning 36.4% adversarial networks 22. 7% computer vision 20.5%	Li et al. (2020b), Tolosana et al. (2020), Verdoliva (2020), Rossler et al. (2019), Matern et al. (2019b), Prajwal et al. (2020), Khalid and Woo (2020), Neves et al. (2020), Fernandes et al. (2020), Yang et al. (2021d), Swathi and Saritha (2021), Amerini et al. (2021a), Agarwal et al. (2021), Dal Cortivo et al. (2021), Schwarcz and Chellappa (2021), Kim et al. (2021b), Bailer et al. (2021), Tariq et al. (2021), Hu et al. (2021), Ahmed and Sonuç (2021), Laishram et al. (2021), Goebel et al. (2021), Han and Gevers (2021), Echizen et al. (2021), Fernando et al. (2021), Kubanek et al. (2021), Huang et al. (2020b), Baek et al. (2020), Zhang et al. (2019c), Pu et al. (2020), Pham et al. (2020), Wang and Dantcheva (2020), Mi et al. (2020), Ranjan et al. (2020), Frank et al. (2020), Yang and Lim (2020), Hashmi et al. (2020), Ranjith Kumar et al. (2020), Xuan et al. (2019), Guan et al. (2019), Kharbat et al. (2019), Bose and Aarabi (2019), Zhang et al. (2019a), Ward (2019)

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