Identification of research trends associated with image capture using machine learning

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Abstract

Image recognition and capture has evolved over the years. From capturing a moment through analog black and white cameras, to detecting objects and motion through the implementation of sensors in different contexts. Currently, image capture devices use different machine learning techniques for motion detection or object recognition in different sectors such as mobility, agriculture, climate, security, among others. Given the diversity of applications of image capture, this research aims to analyze research trends in the application of machine learning in image capture devices in order to guide the planning of future studies. This is done through bibliometrics using the PRISMA2020 decision. As a main result, it was found that since 2020 interest in research on this topic has been increasing. In addition, it is concluded that computer vision and object detection are emerging research topics in which future lines of research can be framed.

Keywords: image acquisition; machine learning; PRISM; sensors; Object detection.

Graphical abstract

Introduction

Image capture devices have gone through various processes and changes that have allowed them to make great strides in the quality of the images captured and in the final application that can be obtained. In principle, the main purpose of image capture was to record historical moments. In this way, towards the nineteenth century, photography changed the way in which the image related to the subject portrayed, breaking with the belief of a constant control of the author in the creation of the image, demonstrating that the influence of nature was also fundamental in this process [1]

Today, digital photography has undergone a remarkable technological advance, moving from analog cameras to high-resolution, low-cost digital cameras. Currently, there are several devices with integrated cameras for image capture and even motion capture. Camera-based object detection is widely used in many fields, including autonomous driving, transportation, robotics, and even medicine. Moreover, today's cameras are not only used to capture flat images, but also to capture video, i.e., motion. For video captured by a moving camera, motion detection is relatively difficult because the movement of the camera and the movement of the object are mixed. [2] [3] [4]

Today, however, with the emergence of new technologies and advances in software, various features of objects can be identified based on images captured by camera hardware using an object detection algorithm. In this way, computer vision and deep learning methods have been studied and applied, allowing not only the correction of the image, but also the adjustment of technical characteristics for air, agricultural, traffic applications, among others. In this sense, video event detection requires first detecting and tracking objects, and then recognizing what is happening around the tracked objects. Therefore, detecting and tracking moving objects play an important role in intelligent surveillance. [3] [5] [6] [4]

When object segmentation is applied to this type of video, the shapes of moving objects are not effectively segmented or detected. Recently, Ferone and Maddalena proposed neural background subtraction for the detection of moving objects in video sequences captured by a pantiltzoom (PTZ) zoom camera. In this algorithm, the background model automatically adapts to variations in the background of the scene that may occur in a typical stationary camera setup or due to PTZ camera movement. However, the center of a PTZ camera (or a camera on a turntable) is still fixed, unlike the center of a moving camera. Therefore, background subtraction would fail for scenes captured by a moving camera. [7] [4] [4]

With this type of technology, the use of these devices has emerged as a potential market in the surveillance and security sector. Therefore, the growing demand for security has led to more research on intelligent surveillance. Smart surveillance has a wide range of applications, such as moving object detection, object tracking, motion segmentation, object classification and identification, event detection, and behavioral understanding and description. The analysis and interpretation of video sequences captured by cameras is an active area of research. Many applications in this area require the initial detection of moving objects in a scene. [8], [9] [10], [11] [12], [13] [14] [15] [16]

However, the surveillance and security industry is not the only one using this type of technology. For example, one of the applications mentioned is the use of cameras as sensors in different contexts. One such application uses spectral index and machine learning to detect harmful algal blooms in water. RGB color sensors have proven themselves over the past four decades as fast, economical, and easy-to-use non-invasive devices for quality assessment in the agricultural and food sectors. [17] [6] [18], [19]

Among these sensors, charge-coupled device (CCD) cameras and flatbed scanners are cost-effective technologies capable of detecting the morphological characteristics of materials, the former being more common for CCD camera applications and providing a large number of frames per second (fps), which is ideal for monitoring various external attributes in industrial environments. Flatbed scanners produce still images that are suitable for developing models for off-line quality assessment of food products. Numerous studies have investigated the possibility of identifying plant varieties or species based on morphological characteristics using color-based imaging. [20] [21] [20]

Novel devices have also been used in the mobility sector, where advanced sensors, such as cameras, radars, and LiDAR, have been considered to monitor traffic and provide more detailed information, such as the number, location, and speed of vehicles, to make more informed decisions at traffic intersections. Examples include Sydney Coordinated Adaptive Traffic (SCATS), Split Cycle Time Optimization and Compensation (SCOOT) Technique, Effective Real-Time Distributed Hierarchical Optimization System (RHODES), experience with adaptive signal control in Germany, and Intelligent Traffic Congestion Control System. Among these advanced sensors, camera-based systems can provide detailed information about traffic conditions cost-effectively thanks to relatively inexpensive camera modules. [22] [23] [24] [25] [26] [3]

Another interesting application of cameras in traffic monitoring and prediction is the detection of drunk driving. This, for the configuration of ignition interlock devices that analyze the driver's alcoholic breath, using a machine learning system to detect drunk drivers based on driver monitoring cameras already integrated into modern vehicles. [27]

On the other hand, there are vision sensors, which are popular in the welding industry because they have the advantages of non-contact, high speed, and large amount of information Robotic vision approaches are mainly divided into active and passive methods Weld bead segmentation based on the passive method usually captures the image of the weld with a CCD camera and then segments the bead into the image [28], [29] [29] [30]

There is also the use of imaging devices for meteorological applications: Sky cameras are devices that provide a hemispherical view of the sky with a temporal resolution that can be less than a minute. The investigations that can be carried out with the camera are very broad and diverse, ranging from cloud detection to aerosol characterization. The most important applications are: optical analysis of aerosol depth, cloud identification and classification, solar resource assessment, and estimation of the three components of solar radiation (global, direct, and diffuse) for which digital image levels have been used. [31] [32], [33] [34], [35] [36] [37]

But satellite remote sensing has not only been used for meteorological applications, new imaging applications have also been generated as a new method to assess water stress in crops. Different satellite platforms have different spatial and temporal resolutions of thermal imagery, such as MODIS, ASTER, GOES, AATSR, SEVIRI, and Landsat. Remote sensing platforms have been used for various applications in agriculture, including surface energy balance estimation of vegetation monitoring, soil moisture measurements, crop water stress detection, and yield estimation. However, its low spatial resolution and long revisit times, mixed pixels, and cloudy weather conditions limit its usefulness for precision agriculture or small farms [38] [39] [40] [41] [42] [43]

In this sense, images are generally considered as discrete pixels and are mathematically rearranged into a two-dimensional matrix (number of pixels × number of bands) when using Continuous Machine Learning (CML) models. The internal processing of a CML model is also done at the pixel level according to a set of sophisticated rules. The positional relationship of the pixels is implicit in the matrix, while the CNN model operates directly on the three-dimensional tens (height × width × bands), making the most of the information in the neighborhood. A CNN generally refers to a class of deep networks that use many convolutional kernels to extract feature maps at different levels [6] [6] [6]

In this way, the various advances and machine learning tools applied to image acquisition devices have made it possible, for example, to use fixed cameras as an auxiliary tool for real-time monitoring and alarms, which has facilitated the use of these cameras in applications such as the detection of illegal fishing activities. In addition, cameras are usually mounted at low heights, surveillance cameras for environmental monitoring and ecological protection, detection of ordinary objects among others. [6] [6] [17], [44] [6]

However, one of the challenges of vision-based methods is image processing, such as edge detection, image filtering, and light fringe extraction. Structured. This is because the correction mechanism is essential to guarantee the accuracy and reliability of the results obtained by capturing the images. [45] [46], [47] [48], [49] [49], [50] [51] One of the biggest challenges, for example, in the application of such technologies in the agricultural sector is temperature correction, which generally includes sensor calibration, environmental calibration, and radiometric corrections. In recent years, artificial intelligence (AI) methods have been widely used to improve detection accuracy through the use of reinforcement learning, deep learning, and machine learning (ML). These approaches have shown promise for improving the accuracy and reliability of thermal data. However, extensive field-scale studies are still needed to fully understand the accuracy of thermal sensors. [51] [52] [53] [54] [51]

In this way, the application of bibliometrics makes it possible to identify areas that require further research and development, and provides an overview of the most common trends and approaches in the application of machine learning in image capture. Consequently, the main objective is to analyze research trends in the application of machine learning in image capture devices in order to guide the planning of future studies. To this end, the following research questions are posed:

PI1: What are the years in which there has been more interest in applying machine learning to vision devices?

PI2: What kind of growth is there in the number of scientific papers on the use of machine learning in imaging devices?

PI3: What are the main research references on the use of machine learning in imaging devices?

PI4: What is the thematic evolution derived from scientific production on the use of machine learning in devices for image capture?

PI5: What are the main thematic groups on the use of machine learning in image capture devices?

PI6: What are the growing and emerging keywords in research on the use of machine learning in imaging devices?

PI7: What topics are positioned as protagonists for the design of a research agenda on the use of machine learning in image capture devices?

Therefore, the article is divided into several sections. Firstly, there is the methodological section, which describes how the study was carried out, the sources of information used, the results obtained and the subsequent discussion. Next, the identified research gaps are addressed and a research agenda is proposed. Finally, the main conclusions are presented.

1. Materials and methods

2.1. Inclusion criteria

In this bibliometric study, the parameters of the PRISMA 2020 declaration were applied to carry out the selection of relevant articles on Image Capture through Machine Learning. Two inclusion criteria were established: firstly, titles and keywords, considered as the main metadata, and secondly, those documents that contain the specific combination between Image Capture and Machine Learning, together with their different citation modes. [55]

On the other hand, during the exclusion process, three phases were carried out in order to guarantee the quality and relevance of the records included in the analysis. In the first phase, all records with erroneous indexing were excluded. In the second phase, documents without access to the full text were excluded, although this phase was only applied to systematic reviews of the literature. It is worth mentioning that in this bibliometric analysis only the metadata of the documents were evaluated. Finally, in the third stage of exclusion, conference proceedings, non-relevant texts and documents with incomplete indexing information were discarded. These exclusion stages ensured the integrity and coherence of the results obtained in this bibliometric research.

2.2. Sources of information

It was decided to use the Scopus and Web of Science databases, which are considered two of the most important and recognized sources of scientific information today. These databases have gained prominence due to their broad multidisciplinary coverage, which includes a wide range of scientific journals, conferences, technical reports, and other types of relevant academic literature. In addition, both Scopus and Web of Science offer advanced search tools and bibliometric data extraction options that facilitate the analysis and comparison of scientific production in the field of study. For the integration and comparison of data between the two databases, a user-friendly method was used, as described in the work of Caputo and Kargina The choice of these two databases ensures a thorough collection of relevant and reliable information to perform a solid and complete bibliometric analysis in this area of research. [56]

2.3. Search strategy

Two specialized search equations were developed, adapted to the previously defined inclusion criteria, as well as to the search peculiarities of the two selected databases. These search equations were designed to optimize the retrial of relevant scientific studies and to ensure the integrity of the search in both databases. In this way, a rigorous and complete search is guaranteed, allowing a complete and up-to-date view of the state of research in the field of image acquisition through the use of machine learning techniques. In this sense, we have the following specialized equations:

For the Scopus database: ((TITLE (camera) AND TITLE ("machine learning")) OR (AUTHKEY (camera) AND AUTHKEY ("machine learning")))))

For the Web of Science database: ((TI= (camera) AND TI= ("machine learning") OR (AK = (camera) AND AK = ("machine learning")))))

d) ***Data Management***

In this research, the Microsoft Excel® tool was used to extract, store and analyze the information obtained from each of the selected databases. Likewise, both the free software VOSviewer® and Microsoft Excel® were used to visualize and graphically represent the different bibliometric indicators. It is important to note that VOSviewer® is a widely recognized tool in the scientific field for bibliometric analysis and data visualization. In this sense, the study of the bibliometric analysis of chemical systems of agricultural soils using VOSviewer® was a relevant reference for the application of this methodology in the present research. With the use of these tools, it would be possible to rigorously and thoroughly analyze the scientific production in the field of image acquisition using machine learning, providing a complete and updated view of trends and advances in this field of study. [57]

2.4. Selection process

It is essential to mention whether an internal automatic classifier was used to support the selection process and whether an internal or external validation was carried out to assess the risk of missing studies or misclassification, as specified in the PRISMA 2020 statement and highlighted in the work of In this context, in the present bibliometric study on machine learning image acquisition, Microsoft Excel-based® automation tools were used as an internal tool. These tools were jointly developed by all the researchers in the study, who then used them independently to apply the established inclusion and exclusion criteria. This approach was adopted to reduce the risk of loss of studies or misclassifications by promoting convergence of the results obtained. The use of these internal tools ensured a thorough and accurate evaluation of relevant scientific papers, thus ensuring the reliability and consistency of the bibliographic selection process. [55]

2.5. Data collection process

In this study, the automation tool used for this purpose was Microsoft Excel®. All authors of this work independently performed the role of reviewers to validate the information extracted from the reports obtained from the two selected databases. A collective data confirmation process was carried out, where an exhaustive and rigorous review was carried out until an absolute convergence of results was achieved. It is also worth noting that the data extraction and confirmation process did not require direct collaboration with the investigators of the included studies, as the relevant information was available in the reports and could be effectively extracted and validated using the automation tool provided by Microsoft Excel®. This approach ensured consistency and reliability in the data collection process and provided a solid foundation for bibliometric analysis in the field of machine learning image acquisition. [55]

2.6. Data Elements

In this bibliometric study on image processing in machine learning, we searched for all the results relevant to the research objectives, which meant following the specific search equations designed for each database. That is, all the articles that mentioned the topic of interest were included. However, if in any case missing or unclear information was found in the texts, these articles were excluded under the category of "non-relevant texts" to ensure consistency and coherence with the purpose and scope of the study. of the study. In this way, it was ensured that only those works that contributed to the understanding of the knowledge base on image capture using machine learning were included, and that the inclusion of incomplete or unclarifying information was avoided.

2.7. Assessment of study risk of bias

A thorough risk of bias assessment of the included studies was carried out to ensure the reliability and completeness of the results obtained. To this end, all the authors of this study actively participated in the data collection process using the automated tool Microsoft Excel®. Similarly, the assessment of risk of bias was carried out jointly and collaboratively by all authors, who independently assessed each included study. The use of the automated tool provided by Microsoft Excel® allowed for a systematic and standardised assessment of risk of bias in each study, thus ensuring the quality and consistency of the results. This robust and rigorous methodological approach guaranteed that the bibliometric analysis was carried out objectively and with high scientific integrity, which strengthens the validity and solidity of the present research.

2.8. Impact measures

The measures of effect used in the synthesis or presentation of the results obtained are specified according to the needs. While these measures are more common in primary research, in the present research, which is based on secondary sources of research, we focus on the analysis of different bibliometric indicators. These included the number of publications on the topic, the number of citations received by each article, and the timing of the use of keywords in the titles and abstracts of the publications. To perform this analysis, tools such as Microsoft Excel® were used for data collection and processing, and VOSviewer® to determine thematic associations and visualize the nodes in the field of study. These bibliometric approaches allowed us to study the temporal evolution and relevance of the topics, as well as to identify the relationships and connections between the different scientific works related to image capture using machine learning.

2.9. Synthesis methods

In the development of bibliometrics on machine learning image capture, several processes were used to select the eligible studies for each synthesis. The intervention characteristics of each study were tabulated and compared with the groups intended for synthesis. In addition, methods were applied to prepare data for presentation or synthesis by imputing missing summary statistics or performing data conversions where necessary. Bibliometric tools of quantity, quality, and structure, as described in the study work, were used to tabulate and visually present the results of the individual studies and syntheses. These bibliometric indicators were applied automatically using Microsoft Excel® to those documents that passed the three previously established exclusion phases. This rigorous and systematized methodological approach allowed obtaining a detailed and objective vision of the scientific production in the field of study and facilitated the clear and understandable presentation of the results obtained. [58]

2.10. Assessment of reporting bias

It is important to consider the risk of bias due to lack of results in a synthesis, which can arise from reporting bias. In the present study, there is the possibility of bias towards certain synonyms found in thesauri such as the IEEE, which is reflected in the inclusion criteria, the search strategy, and the data collection itself. In addition, by limiting inclusion to conference proceedings and excluding non-relevant texts and documents with incomplete indexing, valuable information could be omitted for the complete construction of knowledge on the topic. Identifying and understanding this risk of bias is essential for the correct interpretation of bibliometric results and for a critical and reliable evaluation of scientific production in the field of image processing using machine learning.

2.11. Assessment of certainty

In the context of machine learning imaging, it is important to address the method used to assess the certainty or confidence in the body of evidence of the results obtained. Unlike primary studies, where certainty is assessed on an individual basis, this literature review carries out an overall assessment of certainty. This is achieved through the independent application of inclusion and exclusion criteria and the definition of bibliometric indicators. In addition, the report of the possible biases defined in the methodological design is considered and the limitations of the study in the discussion phase are mentioned. This approach allows us to obtain a more complete and objective view of the body of evidence in the field of study, ensuring a critical and reliable evaluation of scientific production in relation to machine learning image acquisition. Similarly, Figure 1 presents the recommended flowchart in PRISMA2020.

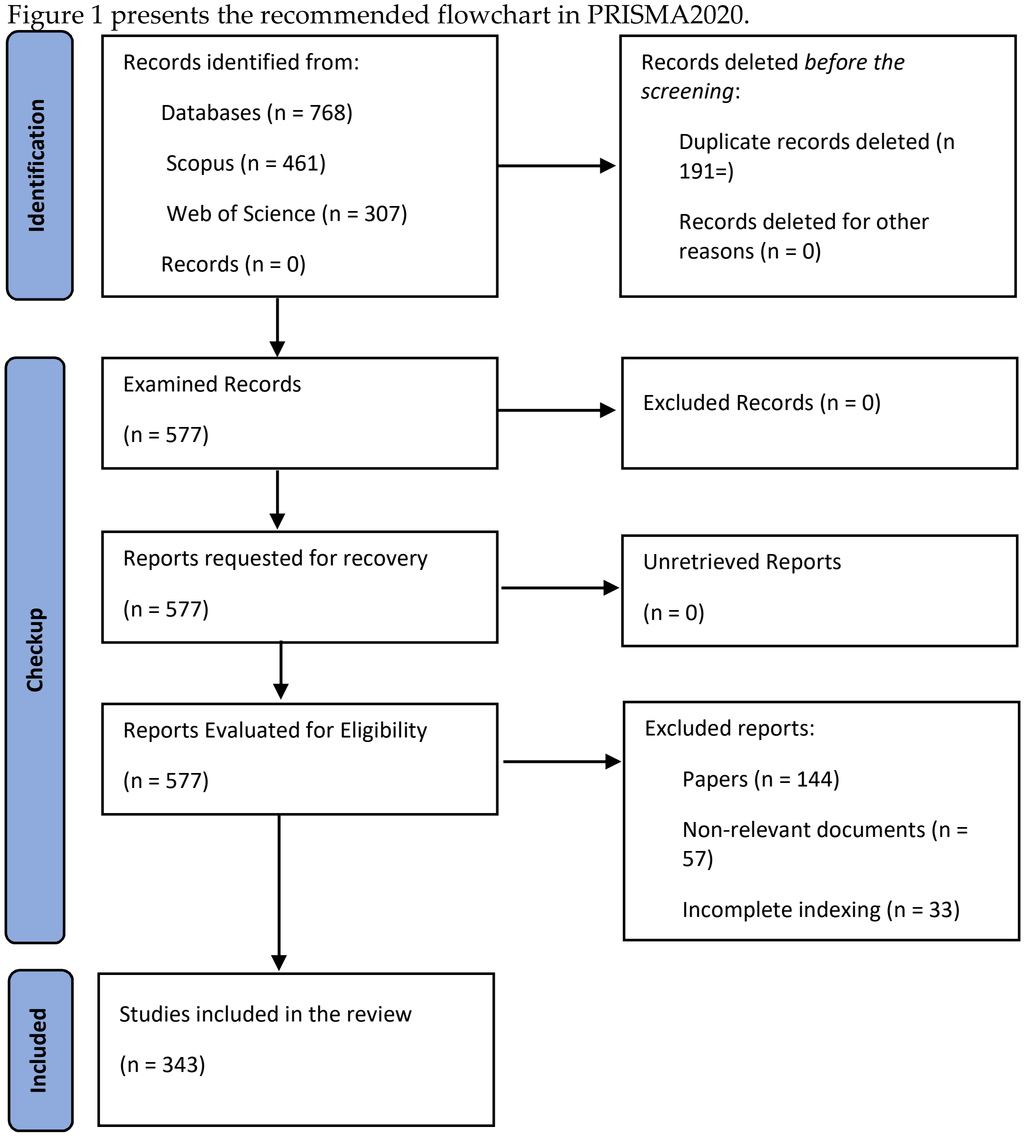

Figure 1. PRISMA flowchart. Own elaboration based on Scopus and Web of Science

This diagram shows the identification phase, product of the application of the search strategy in both databases, as well as the elimination of duplicates. Then the three phases of exclusion and finally the 343 documents that were finally analyzed.

2. RESULTS

First, the annual scientific production is evaluated, based on the number of publications registered each year, as shown in Figure 2. The analysis carried out in this study revealed a growth of the cubic polynomial type with a magnitude of 97.65%. This indicates a significant increase in scientific output related to this topic over time. Specifically, it was observed that the years with the highest number of publications were 2022, 2021 and 2020, suggesting a significant interest and notable increase in research and advances in this field during these periods. These results provide a clear and up-to-date view of the evolution and trends of imaging in machine learning, allowing for a deeper understanding of the state of research in this field.

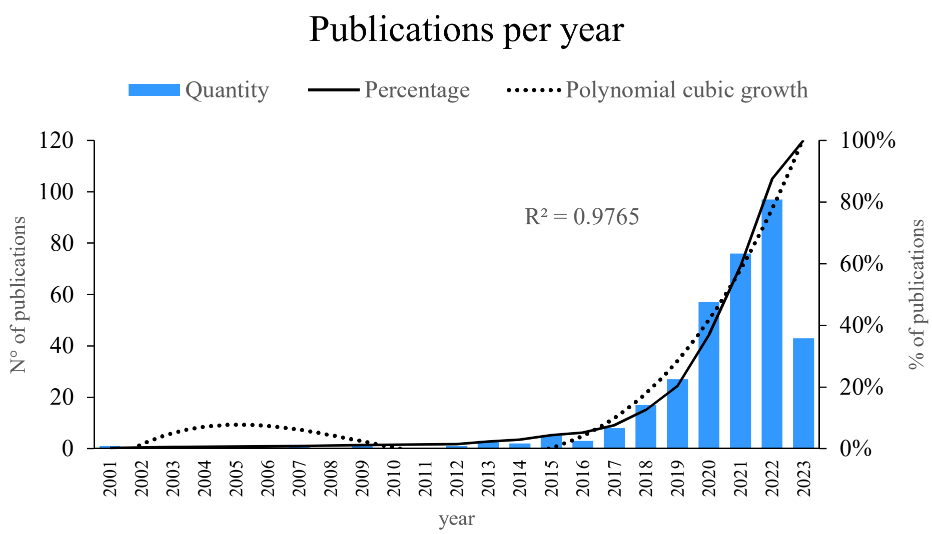

Figure 2. Publications per year. Own elaboration based on Scopus and Web of Science

Bibliometric analysis of machine learning image processing identified two main groups of authors that stand out in the field, as shown in Figure 3. The first group is made up of authors such as Kononenko I, Lu J, Liu AJ, Dong F, Gu F, Gama J and Zhang GQ, who are positioned as benchmarks in terms of impact, despite having a low scientific productivity in terms of the number of publications. On the other hand, the second group of outstanding authors is characterized by high scientific productivity without necessarily having a high number of citations. Authors such as Cenkeramaddi LR and Wang J.

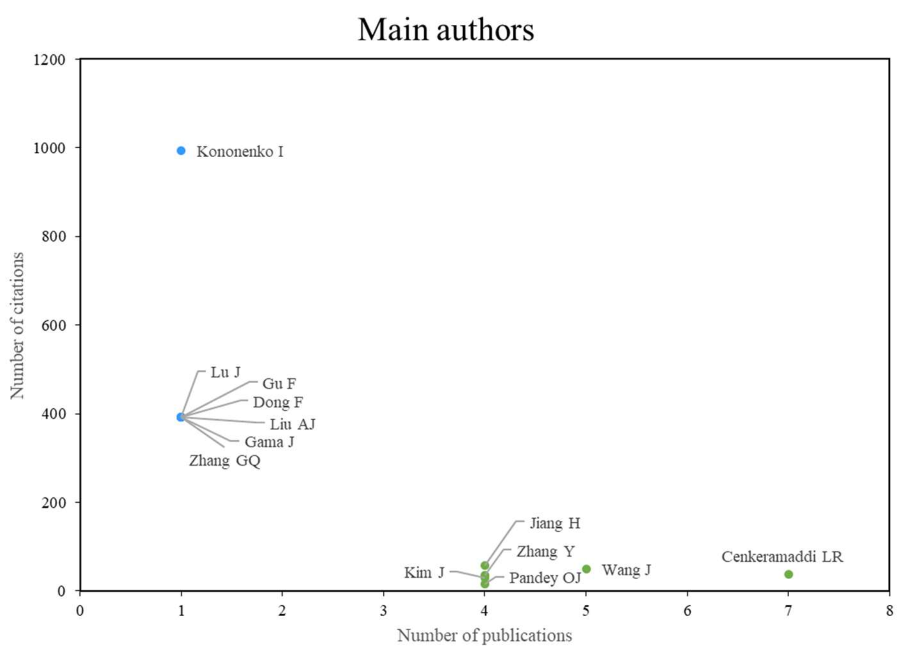

Figure 3. Main authors. Author's calculations based on Scopus and Web of Science.

As for the most important journals, three groups of scientific journals have been identified that stand out in the field, as shown in Figure 4. The first group includes journals such as Sensors and IEEE Access, which are positioned as the most important. They stand out both for their scientific productivity and for their impact, which makes them outstanding references in the scientific community. On the other hand, the second group of journals is characterized by its relevance in terms of impact despite low scientific productivity, and includes journals such as Artificial Intelligence in Medicine and Methods in Ecology and Evolution. Finally, the third group of journals is mainly characterized by high scientific productivity, although their citation counts may be lower than those of other leading journals. In this group, the IEEE Sensors Journal stands out.

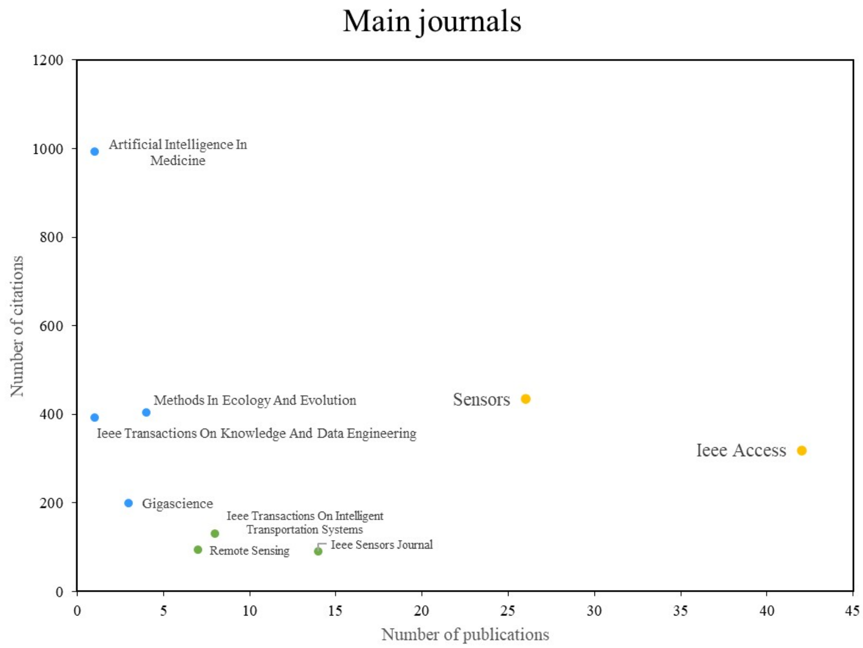

Figure 4. Main magazines. Author's calculations based on Scopus and Web of Science.

In terms of countries, three large groups of countries have been identified that stand out in this area, as shown in Figure 5. The first group includes the United States, Australia, Germany and China, which are the most important for their outstanding scientific productivity and high impact on the academic community. On the other hand, the second group of countries is positioned as a benchmark in terms of impact, despite low scientific productivity, with Slovenia as a prominent example. Finally, the third group of leading countries stands out mainly for its high scientific productivity, although its number of citations may be lower compared to other leading countries. Japan and the United Kingdom stand out in this group.

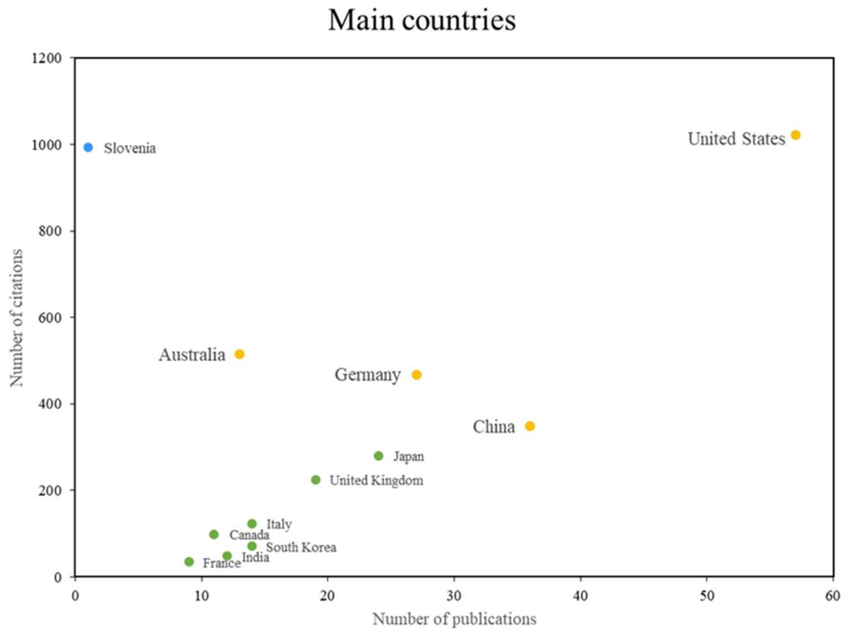

Figure 5. Main countries. Own elaboration based on Scopus and Web of Science

Within the framework of the review of the literature on image acquisition using machine learning, an exhaustive analysis of the thematic evolution in the literature related to this topic was carried out, covering the period between 2001 and 2023, as shown in Figure 6. By examining the most used keyword in each year of research, a significant evolution of the concepts over time could be observed. In particular, in 2001, the emergence of terms such as "prediction reliability" was highlighted, reflecting the first approaches to prediction reliability in the context of machine learning image capture. In contrast, in recent years there has been a preponderance of topics such as "Computer Vision", "Sensors", "Feature Extraction" and "Deep Learning", indicating a clear trend towards research in computer vision. Computer vision, sensors, feature extraction, and deep learning.

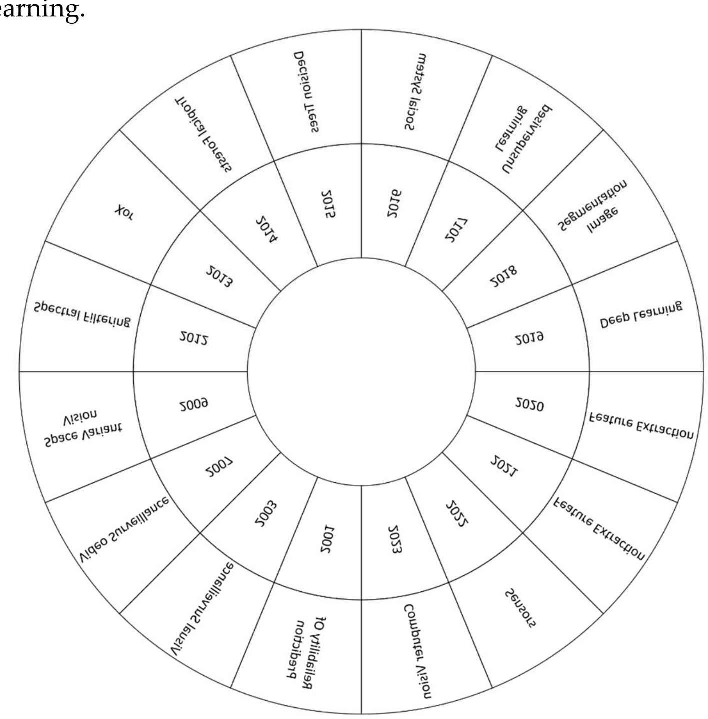

Figure 6. Thematic development. Own elaboration based on Scopus and Web of Science

As for the keyword co-occurrence network in this study, it is found to be organized into a total of 6 different thematic groups, as identified in Figure 7. The red cluster stands out as the most prominent, containing terms such as "Computer Vision", "Detection", "Classification", "Object Detection" and "Image Analysis". It is followed by the green cluster, which includes terms such as "Deep Learning," "Kinect," "Activity Recognition," "Neural Networks," "Data Fusion," and "Convolutional Neural Networks." In addition, other blue, purple, yellow, and light blue color groups were identified that reflect other areas of conceptual affinity in the field of study. These findings provide a visual and structured representation of the thematic relationships and interconnections of keywords in machine learning image capture research, enriching the understanding of the main trends and areas of research in the discipline.

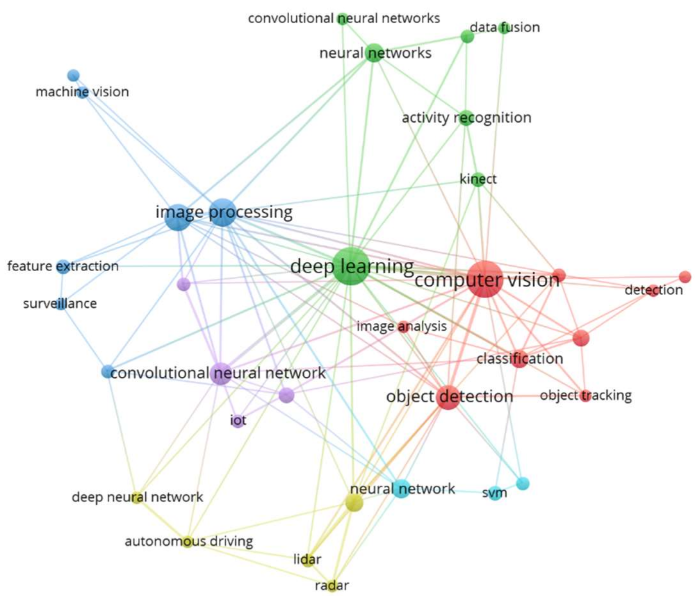

Figure 7. Keyword co-occurrence network. Own elaboration based on Scopus and Web of Science

Figure 8 is presented below, proposing a Cartesian plane where the frequency of use of each keyword on the X axis and the average year of use on the Y axis are represented. This results in four quadrants: the first corresponds to consolidated keywords in the field of study, the second to emerging keywords, the third to declining terms, and the fourth to low-frequency and recently used keywords.

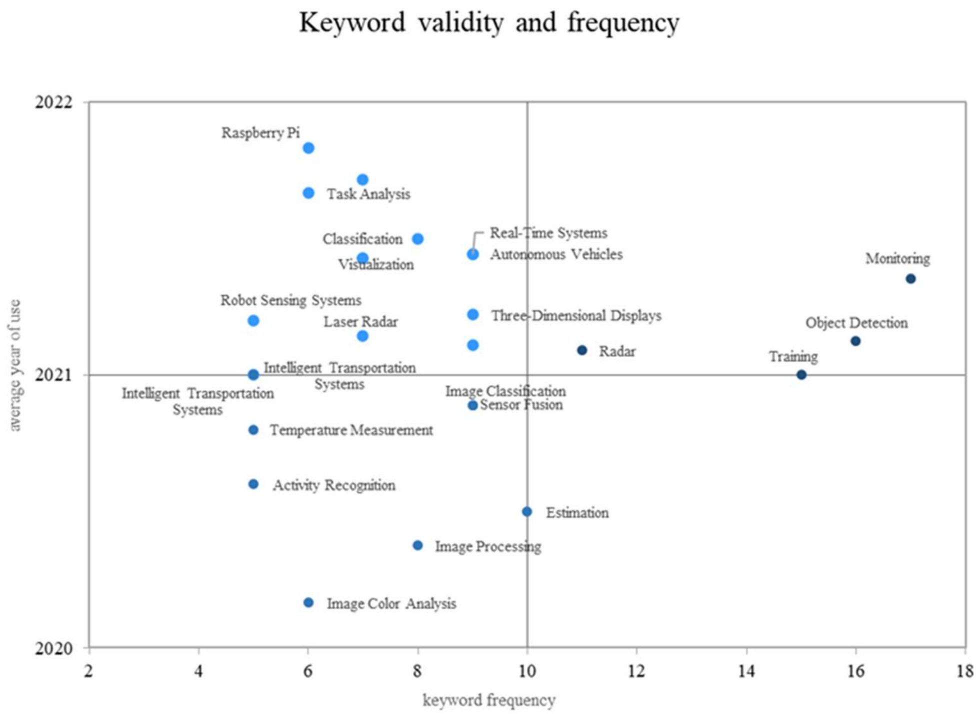

Figure 8. Keyword validity and frequency. Own elaboration based on Scopus and Web of Science

Quadrant 4, characterized by decreasing concepts, contains keywords such as "estimate," the frequency of which has decreased over time. On the other hand, Quadrant 2 shows rare but highly topical words, which become emerging concepts of current relevance, such as "Raspberry Pi", "Task Analysis", "Classification" and "Visualization". Finally, in quadrant 1 are established and growing concepts, such as "monitor ring", "object detection", "training" and "radar", which remain relevant and have seen an increase in use over time.

3. DISCUSSION

4.1. Analysis of the growth of the scientific literature on Image Capture through Machine Learning

This section identifies relevant research on the use of machine learning for image capture in the years 2020, 2021, and 2022. The research addresses a wide range of applications and approaches in this emerging field. In 2022, notable research includes the study by Henriksen et al. on the classification of plastics using online hyperspectral cameras and unsupervised machine learning techniques. This provides an intriguing perspective on the application of advanced technologies in material identification. In 2019, Uma and Eswari proposed an assisted safety and accident prevention system using the Internet of Things (IoT) and machine learning. This addresses a crucial facet in implementing smart technologies for improved safety [59] [60]

In 2021, Hussain et al. conducted a comprehensive review of multi-view video summaries, providing a comprehensive view of the field and highlighting recent trends in video processing. Zhou et al. presented a new method to predict variations in winter wheat yield and protein content using multispectral images taken by unmanned aerial vehicles (UAVs) and machine learning techniques. This represents a significant advance in precision agriculture. Zhou et al. He presented a paper on the reidentification of people that merged multiple characteristics with the learning of adaptive graphs. Their work made remarkable progress in identifying and tracking people in security and surveillance systems [61] [62] [63] [63]

4.2. Analysis of Research References on Image Capture through Machine Learning

As for the most influential authors, two groups emerged: one with a high impact in the field and the other with high productivity. Kononenko I is a notable reference in research due to the influential article titled

'Machine learning for medical diagnosis: history, state of the art, and perspective' Kononenko explored the application of machine learning in medical diagnosis, providing a historical and comprehensive view of the evolution of technology and future prospects in the healthcare field. [64]

On the contrary, Lu J, Liu AJ, Dong F, Gu F, Gama J, and Zhang GQ had a significant impact on the scientific community with their influential review titled 'Learning under concept drift: A review' In this article, the authors address the challenge of conceptual drift in machine learning, offering a comprehensive analysis of the strategies and approaches developed to address this problem. This review is of great value to the research community in the field of machine learning. [65]

Cenkeramaddi LR was recognized for its high scientific productivity. One of the articles that contributed to its prominent position is "Embedded Sensors, Communication Technologies, Computer Platforms, and Machine Learning for UAVs: A Review." This study presents a comprehensive analysis of emerging technologies applied to unmanned aerial vehicles (UAVs), including embedded sensors, communication technologies, computing platforms, and machine learning. The review is of great interest to the research community in the field of UAV imaging. [66]

Finally, Wang J was recognized for his productivity in the field of study. His paper, 'Scaling effects on chlorophyll content estimates with an RGB camera mounted on a UAV platform using machine learning methods', was one of the most notable works. This study investigates the use of RGB images captured by UAVs and machine learning techniques to estimate chlorophyll content in vegetation, which is highly relevant for precision agriculture and crop monitoring. The structure is clear, with logical progression and causal connections between the statements. No changes have been made to the content. [67]

Sensors and IEEE Access are prominent journals in the field of ML imaging due to their high throughput and influence. It is important to note that subjective evaluations have been excluded and that the language used is clear, objective and value-neutral. The text adheres to the conventional structure and formal register, with a precise choice of words and grammatical correctness. The text is balanced and free of filler words and biases. Sensors have made significant contributions to the knowledge of this area through publications such as 'Aerial mapping of pathogen-affected forests using UAVs, hyperspectral sensors and artificial intelligence'. The article discusses the application of UAVs and hyperspectral sensors for the detection of pathogens in forests through the use of artificial intelligence. The article "An End-to-End Deep Neural Network for Autonomous Driving Designed for Embedded Automotive Platforms" presents an innovative perspective on neural networks for autonomous driving, specifically designed for integration into automotive platforms. [68] [69]

On the other hand, IEEE Access, a leading journal in the field of engineering, particularly in electronics, telecommunications, systems and related areas of information and communication technologies (ICT), has contributed to the advancement of this topic. For example, in their publication "A Review of Next-Generation Violence Detection Techniques", they addressed the development of techniques to detect violence in various contexts. In the paper 'Fast and accurate detection of banana fruits in complex bottom orchards', the authors propose a machine learning approach for the rapid and accurate identification of banana fruits in complex bottom orchards. [70] [71]

There are journals that stand out for their impact on the area of knowledge addressed. One such journal is Artificial Intelligence In Medicine, which has made a significant contribution to medical diagnosis with the publication of 'Machine learning for medical diagnosis: history, state of the art and perspective' The article provides a comprehensive review of the use of machine learning in medical diagnosis. In the study 'Machine learning to classify animal species in camera trap images: Applications in ecology' published in Methods In Ecology And Evolution, machine learning was used to classify animal species in images captured by camera traps, which is an important contribution. [64] [72]

In addition, the IEEE Sensors Journal has been very productive with its article on embedded sensors, communication technologies, computing platforms, and machine learning for UAVs. The article presented an overview of emerging technologies for UAVs, including embedded sensors and machine learning approaches. This has generated a great deal of interest within the research community regarding the capture of images by unmanned aerial vehicles. These journals have contributed significantly to the generation and dissemination of knowledge in the field of image capture through machine learning. Its relevance in the results obtained highlights its central role in the advancement and development of research in this field.

Several countries have made significant contributions to the topic of image capture through machine learning. The United States has been a notable benchmark with research such as 'Machine learning to classify animal species in camera trap images'. The text discusses two papers, 'Applications in Ecology' and 'Identification of Animal Species in Camera Trap Images Using Deep Learning and Citizen Science', which focus on the use of machine learning to classify animal species from images captured by photo traps. This research is relevant for applications in ecology and conservation. [72] [73]

Australia has contributed significantly to the generation of scientific knowledge. For example, in the research paper titled 'Learning under concept drift: A review', the authors focused on the challenge of machine learning in environments where concepts change over time. In research titled 'UAVs, Hyperspectral Remote Sensing, and Machine Learning Revolutionizing Reef Monitoring', the authors explore the use of unmanned aerial vehicles, hyperspectral sensors, and machine learning to transform reef monitoring. This has significant implications for marine conservation. Germany is another country that has made significant contributions in this area. For example, the research paper titled "An Invitation to Compressive Detection" delves into the field of signal compression. On the other hand, 'Status Quo and Open Challenges in Vision-Based Sensing and Tracking of Temporary Resources on Infrastructure Construction Sites' deals with the tracking of temporary resources in construction sites using artificial vision. This is relevant for applications in the construction and infrastructure industry. [65] [74] [75] [76]

China has contributed significantly to scientific research, as evidenced by its work on predicting in-field variability in grain yield and winter wheat protein content using UAV-based multispectral imaging and machine learning approaches. This research is crucial for precision agriculture. In the research paper titled 'Real-time classification of rubberwood boards using an SSR-based CNN', the authors present a method for real-time classification of rubberwood boards using an SSR-based convolutional neural network. This method has important applications in the wood industry. [77]

In addition, countries such as Japan, Slovenia and the United Kingdom have made important contributions in this area. Slovenia conducted research on machine learning for medical diagnosis: history, state of the art and perspectives, which has significantly advanced medical diagnosis. Japan has also made notable contributions with work such as 'Computer Vision-Based Phenotyping to Improve Plant Productivity: A Machine Learning Perspective', which focuses on improving plant productivity through computer vision-based phenotyping. Finally, the UK has carried out research on the estimation of non-linear parameters in real time using the Levenberg-Marquardt algorithm in field-programmable gate arrays. This research focuses on the estimation of non-linear parameters in real time and their relevant applications in industrial electronics. These countries have made significant contributions in the field of machine learning imaging, enriching the study. [64] [78] [79]

4.3. Analysis of the thematic evolution of image capture through machine learning

During the early stages of machine learning image capture research, the concept of 'Prediction Reliability' emerged as a fundamental aspect, as stated in . It was emphasized that the reliability of predictions is a crucial factor to consider when applying machine learning techniques in medical diagnosis. The attention paid to this concept allowed us to establish a solid foundation to ensure the accuracy and precision of the results obtained from the machine learning models used in image interpretation. The emphasis on the reliability of predictions provided guidelines for assessing the quality and consistency of results, thus facilitating progress in the application of machine learning techniques in the interpretation of medical images and related fields. [64]

As research has progressed, this conceptual approach has expanded to encompass additional aspects, such as computer vision, sensors, feature extraction, and deep learning. This evolution has allowed for greater diversification in the applications and knowledge generated in this field. The field of image capture through machine learning has expanded to include computer vision, advanced sensors, relevant feature extraction, and deep learning. These concepts have significantly enriched the range of applications and knowledge in this field.

Importantly, computer vision, sensors, feature extraction, and deep learning have played an essential role in today's landscape of the subject. In 2019, there was a significant emphasis on Deep Learning, particularly due to the study conducted by . The study applied a convolutional neural network trained on synthetic data to identify fish species in underwater images. This approach proved to be highly effective and opened up new perspectives for automation and accuracy in the identification of aquatic species. [80]

In 2020 and 2021, the concept of Feature Extraction was the main focus of research, particularly in the work of . This study presents a review of food classification and volume estimation for image-based dietary assessment. The authors discuss the application of trait extraction techniques, which have led to significant improvements in accuracy for food identification and portion quantification. These findings contribute to the development of more effective solutions for diet adherence. In 2022, they used the term "Sensors" in their review of emerging technologies applied to advanced driver assistance solutions (ADAS). The review revealed that the incorporation of sensors and perception technologies is a critical component in the development of ADAS systems, which aim to improve both safety and the driving experience. [81] [82]

Finally, in 2023, he highlighted the focus on Computer Vision in his review of recent advances in thermography and its application through machine learning techniques. Machine vision plays an essential role in the accurate analysis of thermal images, enabling the detection and diagnosis of various conditions and problems in a variety of applications. [83]

4.4. Analysis of the thematic clusters on Image Capture through Machine Learning

Thematic clusters were identified for the network of keywords related to Image Capture through Machine Learning. One of the main groups, characterized by the color red, includes terms such as Computer Vision, Detection, Classification, Object Detection, and Image Analysis. This group suggests a strong thematic affinity between these words, indicating that they are closely related and are frequently used in studies on the topic.

Several studies have investigated the detection of 3D objects from RGBD data using deep learning networks based on Hough voting, including the work of . In addition, it used a realistic dataset and context-based approach to address parking space detection. Similarly, it focused on supervised learning for the recognition of human activities using 2D skeleton data. In addition, in this same group of words is a study conducted by that company that applied machine learning using multiscale classifiers to detect remote phenological patterns in trees in the Cerrado savannah. [84] [85] [86] [87]

The second most relevant group, represented by the color green, includes keywords such as Deep Learning, Kinect, Activity Recognition, Neural Networks, Data Fusion, and Convolutional Neural Networks. These terms demonstrate a strong thematic affinity, suggesting that they are intrinsically related and widely explored in research on machine learning image capture.

Several significant studies have been conducted on the topic, including a survey on imitation learning techniques for end-to-end autonomous vehicles conducted by . On the other hand, he conducted research on body weight estimation to monitor patients while they were lying, standing, and walking using RGBD data. In addition, he introduced a Markov maximum entropy model to recognize human activities with a depth camera. [88] [89] [90]

These studies and the thematic group they form highlight the importance of image capture through machine learning. This field is currently trending due to the use of Deep Learning techniques, Kinect sensors for activity recognition, convolutional neural networks and data fusion. These concepts are fundamental to the advancement of research and development in this area.

4.5. It is a clear and concise title that accurately reflects the content of the text.

Analysis of keyword frequency and validity reveals distinct patterns of evolution in key concepts related to image capture through machine learning. For example, quadrant 4 shows a decrease in the relevance or use of certain concepts compared to previous periods. One such term that is in decline is 'Estimation'. The text suggests that "estimation" was a major research topic in the past in the machine learning imaging literature. However, their interest and use have declined in recent years.

The importance of this term may be related to a study conducted by the study on the estimation of visual odometry in underwater environments using deep learning techniques. The research focused on addressing the challenges of estimating the position and movement of underwater vehicles from images captured in aquatic conditions with limited visibility. The approach aimed to improve the accuracy and reliability of the visual estimation of odometry under difficult conditions, such as the lack of clear underwater visual references. [91]

Although "estimation" was once relevant, its decline in its use suggests that researchers have shifted their focus to emerging concepts such as "Computer Vision," "Deep Learning," "Sensors," and "Feature Extraction." This demonstrates the evolution of the thematic approach in the field of image capture through machine learning and how new research advances are shaping the field.

In quadrant 2, we identify emerging concepts with high potential for relevance today and in the near future. Among these concepts, 'Raspberry Pi', 'Task analysis' and 'Classification' stand out. Raspberry Pi is a programmable device widely used in different applications, mainly sensors, and is an example of an emerging concept in this field. For example, an intelligent monitoring system for controllers was developed using Raspberry Pi. This device has become increasingly popular in the field of image capture due to its versatility and affordable cost. It has the potential to be a powerful tool for future research and applications in the field of computer vision and machine learning, as it can perform image processing and data analysis tasks in real-time. [92]

Task analysis is an emerging concept that has been studied in various researches, including It plays a critical role in the development of autonomous systems by breaking down complex tasks into more manageable steps. In the context of image capture and machine learning, task analysis can be essential to improve the accuracy and efficiency of algorithms and systems that involve image interpretation and classification. [88]

However, I made a small change to improve clarity and fluidity. The text already seems to meet the desired characteristics. I replaced 'On the other hand' with 'In contrast', to better indicate the change in focus from quadrant 2 to quadrant 1. In this quadrant, the term 'Monitoring' refers to the concept that has been widely studied in relation to the monitoring and control of temporary resources in infrastructure construction works. For example, Teizer examined the current status and open challenges in vision-based tracking and temporary resource detection on construction sites, which is crucial to ensure safety and efficiency in construction projects. [76]

On the other hand, object detection is another prominent concept in this quadrant. In relation to this term, a deep learning framework for target detection in thermal imaging was presented to improve firefighting operations. In addition, training is a relevant concept in the field of machine learning image capture. In this case, the focus was on detecting and analysing vehicle taillights at night, as well as training algorithms for this specific task. In addition, the term "radar" is an important concept in quadrant 1, and a new Monte Carlo localization technique was proposed using the fusion of three-dimensional LiDAR and camera data. It is important to note that all language used is clear, objective, and value-neutral, and technical terms are employed consistently. [93]

4.6. Classification of Machine Learning-Based Image Capture Keywords by Function

Based on the main keywords, Table 1 is presented, which describes the tools associated with each keyword, its main applications and key characteristics. This table provides a comprehensive overview of how each tool is used within the field, offering insight into its functionalities and relevance to current research trends and practices.

Table 1. Rank keywords based on their function. The table was created using information from Scopus and Web of Science.

Keyword	Associated tools	Applications	Characteristics
Raspberry Pi	Microcontroller, Camera	IoT Projects, Home Automation	Small, Low Cost, Versatile
Task Analysis	Observation, Interviews	Task Design, Ergonomics	Identify complex tasks, Efficient
Classification	SVM, Neural Networks	Pattern recognition	Sorts data into categories, Accurate
Visualization	Graphs, Diagrams	Data analysis, presentation	Visual representation of information
Monitoring	Sensors, Cameras	Real-time monitoring	Monitor ongoing events or changes
Object Detection	YOLO, SSD	Object detection in images	Locate and classify objects
Training	Backpropagation, gradient descent	Training ML models	Adjust parameters for learning
Radar	Microwave Sensor, Antenna	Navigation, Obstacle Detection	Uses waves to detect objects

4.7. Practical implications

Initially, the focus was on exploring the reliability of predictions generated through machine learning techniques applied in image capture. The study reveals a significant shift in conceptual approaches over time, with a focus on key areas such as computer vision, sensors, feature extraction, and deep learning. This change in theme indicates a growth in maturity and sophistication in the practical implementation of machine learning in image capture.

The results of the primary cluster, identified by the conceptual similarity between terms such as 'Computer Vision', 'Detection', 'Classification', 'Object Detection' and 'Image Analysis', have significant implications for the advancement and consolidation of this field of research. These keywords are essential for image capture using machine learning, including object detection, image classification, and analysis. They are crucial for decision-making and have applications in various fields, such as computer vision, robotics, and medicine.

Analyzing keyword frequency and recency can help identify emerging and declining trends in image capture research using machine learning. The text describes a decrease in the use of the concept of 'Estimation' and an increase in attention towards emerging technologies and task analysis to improve the efficiency and accuracy of the system, as indicated by the emergence of terms such as 'Raspberry Pi', 'Task Analysis', 'Classification' and 'Visualization'. The text describes a decrease in the use of the concept of 'Estimation' and an increase in attention towards emerging technologies and task analysis to improve the efficiency and accuracy of the system, as indicated by the emergence of terms such as 'Raspberry Pi', 'Task Analysis', 'Classification' and 'Visualization'. The text also mentions image capture.

The growing importance of concepts such as "Monitoring", "Object Detection", "Training" and "Radar" is reflected in their increased frequency and relevance in machine learning-based image capture. These areas have significant practical implications in applications such as security, surveillance, anomaly detection, and autonomous system control.

4.8. Limitations

The PRISMA methodology offers valuable insights into the evolution and trends of this field of research. However, it is important to be aware of their limitations, which could affect the interpretation and generalizability of the findings. One limitation is the possibility of bias in the data collected due to the

restricted sources of the Scopus and Web of Science databases. The omission of relevant publications on other platforms or languages could affect the representativeness of the study. In addition, bibliometric analysis tools such as Microsoft Excel® and VOSviewer® may have limitations in terms of data processing and visualization capacity. These tools may not be robust enough to address the complexity of relationships in the keyword co-occurrence network or to perform deeper analysis of patterns and trends.
In addition, while the PRISMA methodology is widely accepted in the scientific literature, it has inherent limitations. For example, the inclusion and exclusion of studies at the screening stage may depend on the judgment of the investigator, which generates bias and affects the reproducibility of the study.

4.9. Research gaps

Based on the analysis of results and trends, Table 2 is presented, highlighting some gaps in research and areas where further exploration is needed. The table also includes specific questions designed to guide future studies to address these gaps, providing clear direction to advance knowledge and overcome existing limitations in the field.

Table 2. Gaps in research. Own elaboration based on Scopus and Web of Science

Category	Gaps in research	Justification	Questions for future researchers
Thematic gaps	1. Integration of machine learning techniques in drones.	Currently, research is mainly focused on using machine learning techniques to capture images. However, there is a gap in the effective integration of these techniques into drone systems. This integration could improve the efficiency and accuracy of image capture.	What are the best ways to incorporate machine learning into drones? How can machine learning experts and drone specialists collaborate more effectively to close this gap?
	2. Application of machine learning in adverse environments.	Research on the application of machine learning in harsh environmental conditions, such as those with variable lighting, extreme climates, or challenging terrain, is lacking. Improving this area could increase the robustness and generalizability of the models.	What are the most effective machine learning methods to address challenges in harsh environments? How can data collection be improved to train models in harsh environmental conditions?
Geographical gaps	1. Research in developing countries.	Most research on machine learning imaging is conducted in	What unique challenges do developing countries face when applying

		developed countries. However, there is a research gap in developing countries, limiting our understanding of the specific challenges and opportunities facing these regions.	machine learning to image capture? How can machine learning solutions be tailored to meet your specific needs?
	2. Regional differences in technology adoption.	Research has not yet explored regional differences in the adoption of machine learning imaging technologies. Understanding these differences could lead to the development of more effective and contextualized solutions.	What factors influence regional differences in the adoption of machine learning for imaging? How can solutions be designed that take into account the particularities of each region?
Interdisciplinary gaps	1. Collaboration between machine learning experts and domain-specific experts.	Effective collaboration between machine learning experts and experts in specific domains, such as ecology, medicine, or agriculture, is crucial. There is a key gap in this collaboration. Fostering this collaboration can improve the applicability and relevance of the results.	How can we improve collaboration between machine learning experts and experts in different domains? What methods of communication and collaboration can facilitate the effective transfer of knowledge between these disciplines?
	2. Ethics in Image Capture with Machine Learning.	The capture and use of images through machine learning must take into account ethical aspects, such as privacy, algorithmic bias, and fairness. Investigating these implications is crucial for the responsible development of technology.	How can we address the ethical challenges related to image capture and use through machine learning? What ethical frameworks and regulations should we take into account when researching and applying these technologies?

Time gaps	1. Analysis of long-term trends in thematic evolution.	Bibliometrics analyzes the thematic evolution in recent periods. However, there is a gap in the analysis of long-term trends. Understanding how the field has evolved over time can reveal broader patterns and perspectives.	What are the main trends in machine learning-based image capture in recent decades? How have machine learning imaging techniques and methodologies developed over time?
	2. Impact of thematic developments on practical applications.	Research is needed to investigate how thematic developments have directly affected applicability and effectiveness.	

4.10. Research agenda

Machine learning is currently used in computer vision. Machine vision is a fundamental tool in the generation of algorithms and techniques that allow computers to interpret, understand and process images in a similar way to humans. Future research may focus on improving the accuracy and speed of machine vision algorithms for specific applications, such as real-time object detection and classification. In addition, future research may focus on generating new models that explore new imaging domains to optimize computational resource consumption.

The use of artificial intelligence can improve the accuracy and reliability of image capture models, especially in complex and challenging contexts. To improve the perception and decision-making of real-time machine vision systems, such as autonomous vehicles, it is important to explore the incorporation of AI.

This includes the use of radars. The use of radar technology in machine learning-based image capture could prove beneficial in scenarios with restricted optical visibility, such as adverse weather conditions or regions with visual obstructions. This would improve the detection and location of objects in such difficult conditions. It is also possible to combine radar data with other sources, such as RGB or LiDAR cameras, to gain a more complete understanding of the environment and improve the robustness of the system.

Estimation involves predicting values or characteristics from the input data. Future research may focus on developing more accurate and reliable estimation algorithms for specific applications, such as estimating parameters in machine vision systems or estimating physical properties in remote sensing images. In addition, exploring the incorporation of uncertainty and error propagation techniques in estimation models can facilitate decision-making based on the results obtained.

This can be achieved through the use of Deep Learning. Deep learning enables the development of more complex models that can learn hierarchical representations of features. In the future, challenges such as interpreting and explaining deep learning models can be addressed to understand their decision-making logic and motivation. In addition, the research could explore the integration of deep learning with other techniques, such as reinforcement learning or knowledge transfer, to improve the performance of models in image capture tasks.

Autonomous vehicles are an emerging area of research due to the growing demand for autonomous driving systems in the transportation industry. Currently, object recognition algorithms are being developed to enable autonomous vehicles to detect and recognize objects in real-time, such as pedestrians, vehicles, and obstacles in their environment. Future research should prioritize improving the accuracy of algorithms to ensure safe driving in various conditions and scenarios. In addition, exploring data fusion techniques to integrate information from different sensors can lead to a more complete perception of the environment.

Object recognition has become increasingly relevant due to its applications in security, robotics, and healthcare. Currently, deep learning techniques, including convolutional neural networks, are being developed and optimized to achieve more accurate object detection and recognition. As a future research direction, we could explore methods to improve object recognition under challenging conditions, such as low-resolution images, variable lighting, or environments with high object density. Transfer Learning and Reinforcement Learning techniques can be used to adapt object recognition models in ever-changing environments.

The term "real-time system" is relevant due to the need to process and analyze real-time image data for critical applications such as object detection in autonomous vehicles and surveillance systems. Because of these factors, developers are creating algorithms and architectures optimized to achieve real-time image processing with low latency. Future research could focus on improving the efficiency and speed of real-time systems through the use of specialized hardware accelerators and parallelization techniques.

Optimization refers to the application of techniques such as genetic algorithms and gradient descent to adjust model parameters and improve performance. Future research could focus on developing optimization algorithms to address complex problems and large data sets. In addition, researchers can explore multi-objective optimization approaches to balance different aspects of system performance, such as accuracy and speed, for optimal solutions for real-time applications.

Sensor fusion: The fusion of information from multiple sensors allows for a more complete and accurate perception of the environment. This is crucial for applications such as autonomous vehicles, driver assistance systems, and intelligent surveillance. The research has focused on the development of machine learning algorithms and data fusion techniques to improve the robustness and reliability of the system. Future studies should focus on developing advanced and efficient sensor fusion methods capable of handling data from multiple sensors. In addition, it is possible to investigate how the integration of Deep Learning and Reinforcement Learning techniques can improve the adaptability and learning of Sensor Fusion systems.

This section refers to image processing. Image processing techniques are commonly used to pre-process images before applying machine learning algorithms. This includes noise removal, contrast enhancement, and edge detection. In addition, these techniques are used to extract relevant features from images, which is crucial for tasks such as object detection and activity recognition. Future research could explore combining classic image processing approaches with deep learning techniques to achieve more accurate results. In addition, novel methods for real-time image processing may be worth exploring, particularly in high-performance contexts such as autonomous vehicles and intelligent transportation systems.

Activity recognition is another area of interest, where deep learning algorithms and image processing techniques are being developed to identify and categorize human activities, such as walking, running, or driving. This is relevant in applications such as traffic monitoring systems and the detection of anomalous behavior. Future studies should aim to expand the ability to recognize more complex activities, such as specific sports or social interactions. This could be achieved by integrating data from different sensors, such as cameras and inertial sensors, which can improve the accuracy and reliability of real-time activity recognition.

In addition, Intelligent Transportation Systems (ITS) should be considered. ITS (Intelligent Transportation Systems) rely on image capture technologies, such as cameras and radars, to monitor traffic, detect events, and improve road safety. Future research may focus on developing smarter, more adaptable ITS systems that use machine learning techniques to make informed decisions and predict traffic patterns. In addition, Deep Learning and Reinforcement Learning algorithms can enhance the development of ITS systems to adapt to various conditions and scenarios. Finally, Figure 9 is presented, which consolidates the key areas for future research based on the findings, highlighting emerging trends and potential gaps identified during the analysis.

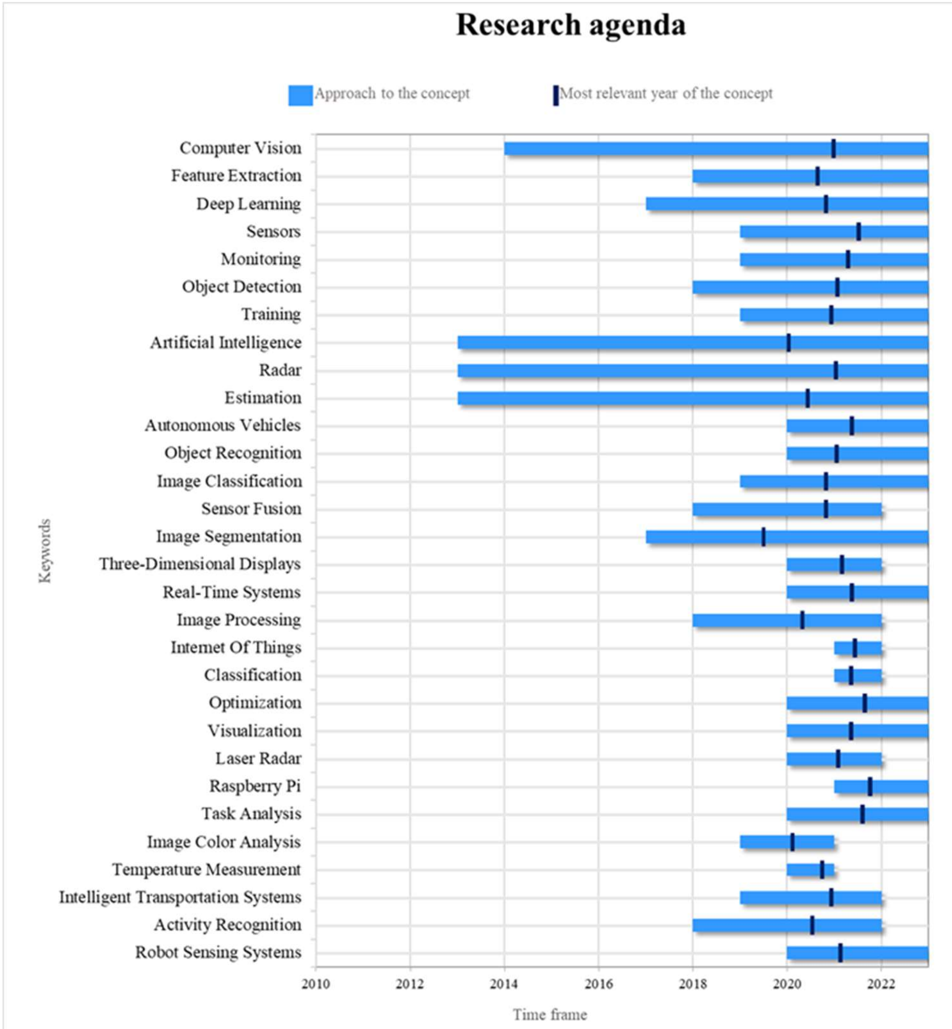

Figure 9. Research agenda. Own elaboration based on Scopus and Web of Science

4. Conclusions

It can be concluded that the years of greatest interest in the field of Image Capture through Machine Learning are 2022, 2021 and 2020. This indicates a steady growth and continued attention to this area of study in recent years. The number of scientific papers related to Machine Learning Image Capture has increased following a cubic polynomial trend, reflecting the dynamics and growing importance of this field of research.

Prominent researchers in this field include Kononenko I, Lu J, Liu AJ, Dong F, Gu F, Gama J, and Zhang GQ. The most influential journals in this area are Sensors and IEEE Access. In addition, the United States and Australia are leaders in scientific production, indicating their important contributions to the advancement of knowledge in this field. The evolution of topics in image capture through machine learning has undergone significant changes over time. Initially, the focus was on "prediction reliability," but it has since expanded to include more diverse and broader topics, such as "computer vision" and "sensors." This transition indicates a maturation in the field. Researchers are now exploring more diverse and complex applications of machine learning techniques in image analysis. This promises significant advances in areas such as object detection, pattern recognition, and visual data analysis.

The main thematic clusters identified consist of terms such as 'Computer Vision', 'Detection', 'Classification', 'Object Detection' and 'Image Analysis'. These terms reflect a strong conceptual affinity between key terms related to image capture and processing using machine learning techniques. This indicates that researchers are addressing interrelated topics in their research, which facilitates the development of integrated solutions in this field. These groups can serve as a guide for future interdisciplinary research and collaborations.
Emerging and emerging keywords, such as 'Raspberry Pi', 'Task Analysis', 'Monitoring', 'Object Detection' and 'Training', indicate new directions and approaches in the research and learning of automatic image capture. These emerging concepts suggest a growing interest in the application of specific technologies, such as the Raspberry Pi, and in areas of study, such as task analysis and system optimization. Keyword identification presents opportunities to explore innovative approaches and address current challenges in this field. For example, it can help improve object detection systems and optimize real-time training algorithms. These emerging topics can drive new lines of research with potential applications in various industries and scientific fields.

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