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Examining the Global Patent Landscape of Artificial Intelligence-Driven Solutions for COVID-19

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Abstract: Artificial Intelligence (AI) technologies have been widely applied to tackle Coronavirus Disease 2019 (COVID-19) challenges, from diagnosis to prevention. Patents are a valuable source for understanding the AI technologies used in the COVID-19 context, allowing the identification of the current technological scenario, fields of application, and research, development, and innovation trends. This study aimed to analyze the global patent landscape of AI applications related to COVID-19. To do so, we analyzed AI-related COVID-19 patent metadata collected in the Derwent Innovations Index using systematic review, bibliometrics, and network analysis., Our results show diagnosis as the most frequent application field, followed by prevention. Deep Learning algorithms, such as Convolutional Neural Network (CNN), were predominantly used for diagnosis, while Machine Learning algorithms, such as Support Vector Machine (SVM), were mainly used for prevention. The most frequent International Patent Classification Codes were related to computing arrangements based on specific computational models, information, and communication technology for detecting, monitoring, or modeling epidemics or pandemics, and methods or arrangements for pattern recognition using electronic means. The most central algorithms of the two-mode network were CNN, SVM, and Random Forest (RF), while the most central application fields were diagnosis, prevention, and forecast. The most significant connection between algorithms and application fields occurred between CNN and diagnosis. Our findings contribute to a better understanding of the technological landscape involving AI and COVID-19, and we hope they can inform future research and development's decision making and planning.

Keywords: artificial intelligence; COVID-19; patents; systematic review; bibliometrics; network analysis

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Citation: Mota, F.; Braga, L.A.M.; Cabral, B.P.; Ferreira, N.C.d.S.; Pinto, C.D.; Coelho, J.A.; Alves, L.A. Examining the Global Patent Landscape of Artificial Intelligence-Driven Solutions for COVID-19. *Mach. Learn. Knowl. Extr.* **2024**, *6*, 1619–1632. https://doi.org/10.3390/make6030078

Academic Editor: Andreas Holzinger

Received: 19 January 2024
Revised: 3 May 2024
Accepted: 10 May 2024
Published: 16 July 2024

1. Introduction

Artificial Intelligence (AI) is an interdisciplinary field spanning different research areas where algorithms mimic human cognitive functions such as learning and problem-solving [1,2]. AI-related algorithms encompass, e.g., Machine Learning (ML) [3] and Deep Learning (DP) [4]. The former is a type of AI that allows machines to learn from data using pattern recognition, and the latter is a subset of ML that utilizes neural networks to model and solve complex problems [4]. Concerning the learning capabilities of these algorithms, AlphaGo Zero—a computer program developed by Google subsidiary DeepMind to play the board game Go—is a good example of algorithm learning without human intervention or input [5].

In healthcare, they have been used in various contexts, including medical image analysis, disease diagnosis, and drug discovery [6]. Despite promising results, randomized clinical studies are considered vital to validate ML as a standard procedure in medical practice [7]. Recently, we have seen growing adoption of these technologies in response to the Coronavirus Disease 2019 (COVID-19) pandemic [8]. COVID-19 has had a major impact on global health and economies, and AI-based solutions are being used to aid in its diagnosis [9], monitor its spread [10], and develop effective vaccines [11]. However, the reach that AI will still have on COVID-19 in the years to come is still to be known.

What can we then expect from AI use in COVID-19-related applications in the near future? This study addresses this question by mapping the patents related to AI and COVID-19. As it is known, patent records provide detailed information on inventions that may or may not reach the market at any time in the future. It also reveals companies' stock of knowledge, as well as research and technology strategies and trends [12,13]. Thus, assisting decision makers in formulating innovation strategies and identifying inventions of interest and technological opportunities [14,15]. Furthermore, patents offer unique insights into the tangible innovations and technological advancements in a given domain [14]. By analyzing patents, we gain access to proprietary information, novel methodologies, and potential commercial applications that may not be fully captured in the academic literature [14]. Globally, patents are widely used as proxies for innovations and are often indicative of significant research and development investments [15]. Therefore, analyzing patents provides a robust foundation for understanding the state of AI-based solutions for COVID-19 from both technological and commercial perspectives.

To achieve the study's aim, we performed a systematic review and a bibliometric and network analysis using metadata of patent records related to AI and COVID-19 collected in the Derwent Innovations Index (DII). The systematic review was based on the PRISMA [16,17] and the RIPL [18] statements. The former is a reporting checklist of information to be included in systematic reviews and meta-analyses, primarily designed to report evaluations of health interventions [16,17], and the latter is a reporting checklist of information for patent landscape articles [18]. Bibliometrics uses statistics to evaluate documents' metadata, such as articles and patents. In turn, network analysis uses mathematics, graph theory, and statistics to evaluate the metadata of the same type of document but via the analysis of co-occurrences between variables, reporting the results visually through network layouts [19].

As of April 2024, over five thousand scientific publications (all document types) were somehow related to AI and COVID-19 indexed in the Web of Science Core Collection. Only fifty scientific publications used bibliometrics, and thirty-three used network analysis. Just two scientific publications combined bibliometrics and network analysis. None of them assessed patent metadata. One hundred and nineteen scientific publications performed systematic reviews, none with patents. Then, our study contributes to the scientific literature by providing a global patent landscape of AI- and COVID-19-related inventions. Additionally, it is advanced in terms of methodological terms by combining three different approaches to evaluate patent metadata: systematic review, bibliometrics, and network analysis. Therefore, we hope that our study may shed some light on the inventions related to AI and COVID-19 that are being protected by organizations and individuals worldwide and perhaps can enter the market in the coming years. The search strategies used to identify these publications are available in the Supplementary Material.

Besides this introduction, this study is divided into four more sections. The Section 2 presents the methods used in the research and the limitations of the study. The Section 3 presents the results of the systematic review and the bibliometric and network analysis, followed by the Section 4 discussing the results of the study. The Section 5 presents the study's conclusions.

2. Materials and Methods

2.1. Systematic Review

The metadata of patent families was identified and collected in the Derwent Innovations Index (DII). A patent family refers to a group of patent applications that share the same or similar technical content and are linked through priority claims (European Patent Office: https://www.epo.org/index.html (accessed on 10 May 2024)). Table 1 depicts the search strategies. We used descriptors of AI and COVID-19 collected in the Medical Subject Headings (MeSH: https://ncbi.nlm.nih.gov/mesh/(accessed on 10 May 2024)). MeSH is the controlled vocabulary thesaurus of the National Library of Medicine, National Center for Biotechnology Information (NLM/NCBI), used for indexing PubMed articles. The timespan was set to retrieve records of patents published in DII between 1 January 2020 and 31 December 2022. Strategy #1 searches for AI in the titles (TI) and COVID-19 in the titles and abstracts (TS) of the patents, while strategy #2 narrows the scope of the strategy by searching for AI and COVID-19 only in the title (TI) of the patents. Search #3 shows that #2 is contained in #1, and #4 excludes from #1 the records belonging to #2. The search and data collection were performed on 4 January 2023.

Table 1. Search strategies applied in DII time.

Set	Query	Timespan	Records of Patents
#4	#1 NOT #2		83
#3	#1 OR #2		170
#2	TI = ((“Artificial Intelligence” OR “Computational Intelligence” OR “Machine Intelligence” OR “Computer Reasoning” OR “Computer Vision System*” OR “Machine learning” OR “Transfer Learning” OR “Deep Learning” OR “Hierarchical Learning”) AND (“COVID-19” OR “SARS-CoV-2” OR “2019 Novel Coronavirus” OR “2019-nCoV” OR “Coronavirus Disease 2019” OR “Severe Acute Respiratory Syndrome Coronavirus 2” OR “SARS Coronavirus 2”))	1 January 2020 to 31 December 2022 (Publication Date)	87
#1	TI = (“Artificial Intelligence” OR “Computational Intelligence” OR “Machine Intelligence” OR “Computer Reasoning” OR “Computer Vision System*” OR “Machine learning” OR “Transfer Learning” OR “Deep Learning” OR “Hierarchical Learning”) AND TS = (“COVID-19” OR “SARS-CoV-2” OR “2019 Novel Coronavirus” OR “2019-nCoV” OR “Coronavirus Disease 2019” OR “Severe Acute Respiratory Syndrome Coronavirus 2” OR “SARS Coronavirus 2”)	1 January 2020 to 31 December 2022 (Publication Date)	170

The raw records of queries #2 and #4 were imported in plain text format into the data/text mining software VantagePoint 11.0 for treatment and analysis. We checked for duplicated records using the VantagePoint tool “Remove Duplicated Records” and the DII field “Derwent Primary Accession Number” (PAN—a unique identification number of patent records assigned by DII) and found no duplicated records.

We automatically included the 87 records of query #2 and assessed for eligibility the 83 records of query #4. The DII Abstract is structured, and most of it contains the fields novelty, use, and advantage. Other fields that may be present are Description of Drawings and “Detailed Description—an Independent Claim”. From the 83 records in query #4, we automatically excluded 34 records that did not contain at least one MeSH Term related to COVID-19 in the Abstract Use field. This field of the abstract was chosen because it describes the application/use of the invention. We checked the 34 excluded records and re-included 12 records that were automatically excluded due to typos or variations in COVID-19-related terms (COVTD-19; Coronavirus Disease 19; Coronavirus Disease-19; Coronavirus; Corona virus; Coronavirus disease; COVID). As a result, we included 61 records from query #4. Next, we created a dataset containing the records of all 148 patents from queries #2 and #4 and downloaded the full document of these patents (in PDF format) in the Derwent World Patents Index (DWPI). Then, by reading the PDFs of the 148 patents, one author (NF) manually screened the patents for eligibility, excluding three records considered unrelated to the study’s subject.

The same author classified the selected records according to their application field and AI-related algorithm. The AI-related algorithms cited by the patent inventors were classified as DL [20–22], ML [23–25], and AI [26,27]. We considered that DL is encompassed by ML, which in turn falls under the broader field of AI [28]. A second author (CP) reviewed all selected and excluded records and the classification. The disagreements were resolved in a consensus meeting, where these two authors reviewed the classification of 34 patents and excluded 3 more patents. Then, the final dataset contains 142 patent records. The list of basic patent numbers of the included and excluded patents is available in the Supplementary Material.

2.2. Bibliometrics and Network Analysis

The bibliometric and network analysis was carried out in VantagePoint 11.0 using the dataset of 142 patent records of the systematic review. Data were collected from the fields of priority years, priority countries, patent assignees, and the International Patent Classification (IPC). The IPC is a hierarchical classification system of patents based on their technical subject matter. It assigns a unique code to each patent document, allowing searching and analysis of patent information (World Intellectual Property Organization: https://www.wipo.int/classifications/ipc/en/ (accessed on 10 May 2024)).

We classified the patent assignees as people and organizations using the hyphen and the last letter of their codes (e.g., using "-C" to classify as organizations assignees with codes like ULVP-C and IBMC-C, and "-I" to classify as people assignees with codes such as KUMA-I, and SHAR-I). Additionally, we identified among the organizations the assignees linked to academia using "univ," "coll," "inst," and "found" as keywords.

Using VantagePoint 11.0, we created a co-occurrence matrix of IPC, which was imported into the network analysis software Gephi 0.10. This software was used to build the networks of IPC and the two-mode network of AI-related algorithms and application fields and calculate the network metrics. A two-mode network is a type of network in which the data involve two levels of analysis, and the co-occurrences between and within categories are considered [29]. In the IPC network, weighted degree centrality (WDC) gives the size of the nodes, colors, and edges' thickness. In the two-mode network, WDC gives the size of the nodes and the edges' thickness, but the nodes are colored according to their level (AI-related algorithms are gray, and application fields are blue). WDC is the sum of the weights of all edges connected to a node [19]. The force-directed layout algorithm Fruchterman–Reingold (Gephi: github.com/gephi/gephi/wiki/Fruchterman-Reingold (accessed on 10 May 2024)) gives the networks' layout. In addition to WDC, we used the following network metrics to evaluate the network: (i) degree centrality (DC is the number of edges a node has); (ii) closeness centrality (CC measures how close a node is to all other nodes); (iii) betweenness centrality (BC measures the shortest path of a node to connect to others); and (iv) eigenvector centrality (EC measures the connections a node has with central nodes) [19]. All network results and IPC code descriptions are available in the Supplementary Material. The descriptions of IPC were generated automatically using VantagePoint's thesaurus IPC8.the. Additionally, the descriptions of the codes can be consulted on the website of the World Intellectual Property Organization (WIPO: www.wipo.int/classifications/ipc/en/ (accessed on 10 May 2024)). The frequency graphs were generated in GraphPad Prism 8, the network figures in Gephi 0.10, the IPC sunburst codes in VantagePoint 11.0, and the AI algorithms' figure in Canva.

2.3. Limitations of the Study

On one hand, the three-year period posed a challenge to the bibliometric and network analysis since it is a very short timespan to assess variables such as the evolution of annual patenting and patent assignees. Therefore, this mapping lacks some common analysis often seen in bibliometric and network analysis. Anyway, the period is coherent with the beginning of the COVID-19 2019 pandemic. On the other hand, the three-year period consisting of only 142 patents was decisive in allowing us to perform the systematic review.

Although the full document of patents was consulted, the application field classification was mostly based on reading DII rewritten patents titles and abstracts. The full documents were more relevant to perform the algorithm classification.

3. Results

3.1. Systematic Review

The classification of AI-related algorithms is shown in Figure 1. The 142 patents analyzed use AI algorithms, of which 124 use one or more ML algorithms and 78 specifically use DL algorithm. It is important to emphasize that the 78 DL-related patents are counted among the 124 ML-related patents and, consequently, are counted in the total number of patents using AI (n = 142). There were 18 patents that did not directly cite the use of ML or DL algorithms, and they were classified as AI. The algorithms listed in Figure 1 have been cited in at least one patent record.

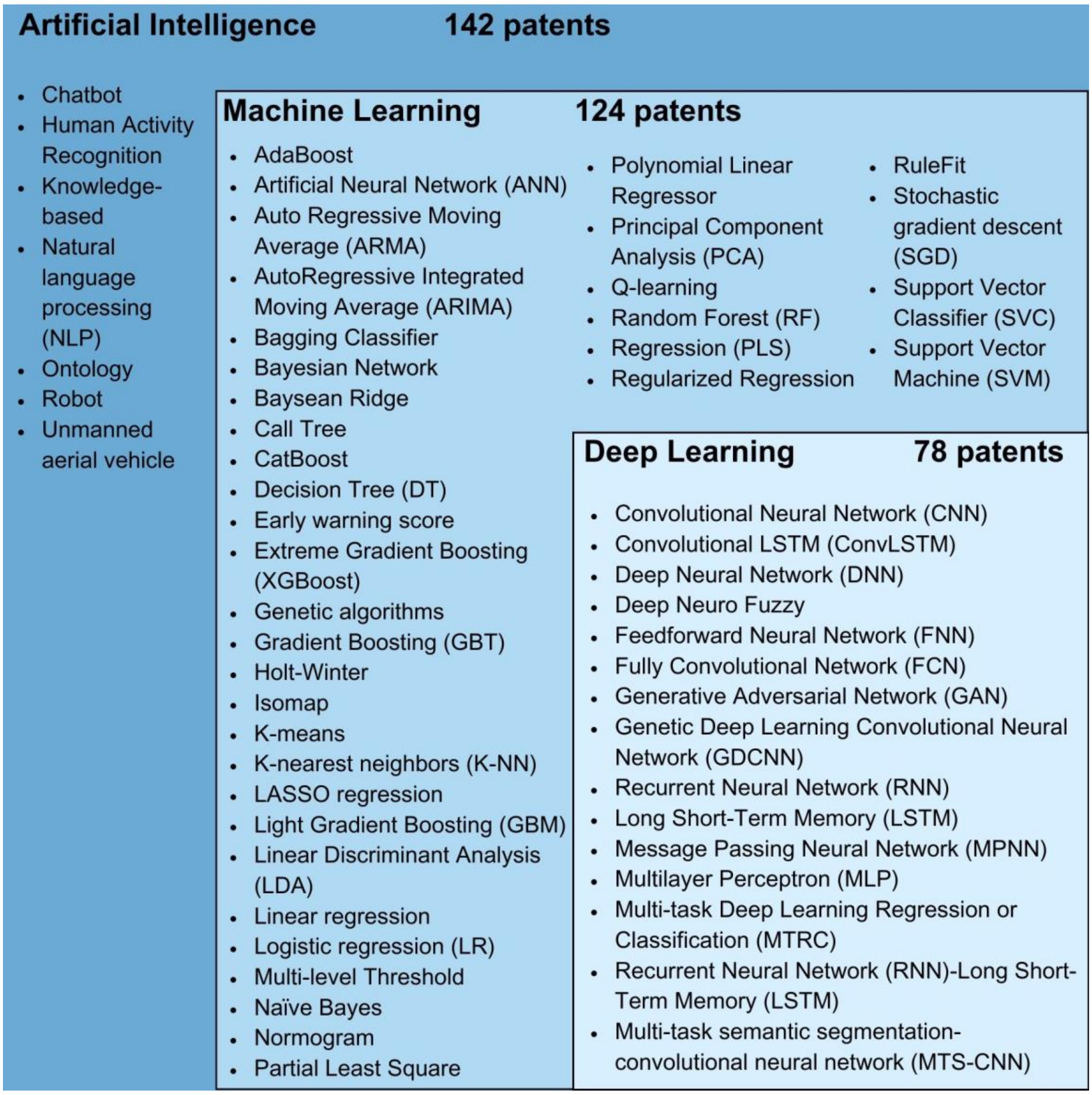

Figure 1. Patent records' classification into AI subgroups. All 142 records were classified as AI-related, citing AI in general, or algorithms such as chatbot and NLP or ML or DL. Of these, 124 records were classified as ML-related for citing ML, DL, or their related algorithms. Moreover, 78 records were classified as DL-related for specifically citing DL or its related algorithms.

The most cited algorithm was Convolutional Neural Network (CNN), which was cited in 36.62% of the patent records, followed by Support Vector Machine (SVM) (14.79%) and

Random Forest (RF) (9.86%) (Figure 2a). Among the patent records citing the use of CNN, there are methods (IN202111029075; US11087883) and devices, such as a digital stethoscope (IN202141044612) for diagnosing COVID-19. An example of an SVM patent record is a system for mortality prediction based on the infected patient's data (IN202141055989). A method for epidemic prediction in cities based on space, time, and social media data (CN113724886) is an example of RF use related to COVID-19.

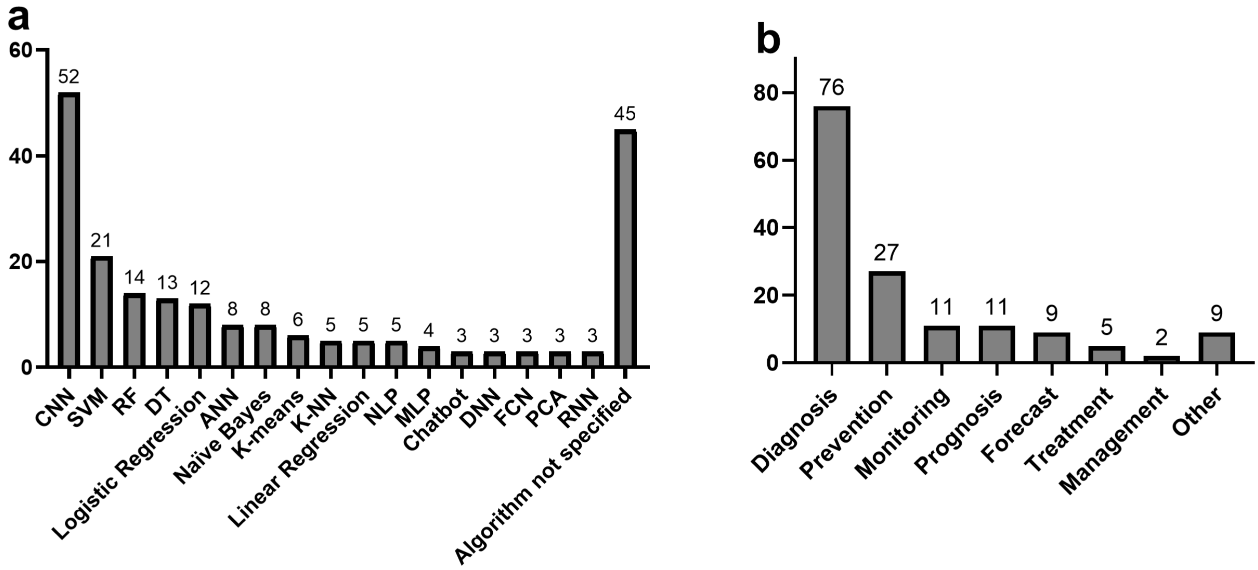

Figure 2. Patent records' classifications into AI-related algorithms and application fields. (**a**) Most frequent AI-related algorithm (higher or equal to three). (**b**) Most frequent application fields. Algorithm abbreviations: Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Artificial Neural Network (ANN), K-nearest neighbors (K-NN), Natural Language Processing (NLP), Multilayer Perceptron (MLP), Deep Neural Network (DNN), Fully Convolutional Network (FCN), Principal Component Analysis (PCA), and Recurrent Neural Network (RNN).

Regarding the patent application fields (Figure 2b), diagnosis is the most frequent (53.52%), followed by prevention (19.01%). Most diagnosis patent records use DL algorithms (77.63%), such as CNN and Fully Convolutional Network (FCN). These algorithms are mainly used for image-based diagnostics, relying on the analysis of X-ray (IN202141043919; AU2021105028) and computed tomography (CT) (IN202241000074; AU2021100007) chest images. Prevention patent records mainly use ML algorithms (70.37%), such as Artificial Neural Networks (ANNs) and K-means. Examples include systems designed to predict the spread of COVID-19 based on demographic and vaccination history data (IN202141047868) and software designed to provide personalized guidelines to individuals for improving resistance against COVID-19 (IN202141053891).

3.2. Bibliometrics and Network Analysis

Most patents were filled in 2021 (56.34%). Due to a delay in indexing patent records in DII, the number of records filled in 2022 (43) may have probably increased throughout 2023. India (IN) was the priority country of 61.97% of the patents, followed by the United States (US: 13.38%) and Australia (AU: 12.68%). About 65% of the patents belong to people. The other assignees were classified as organizations. Among the 55 organizations, 58.18% are universities, colleges, institutes, or foundations.

The three most frequent IPC codes are G06N-020/00 (29.58%), G16H-050/20 (29.58%), and G06K-009/62 (26.06%) (Figure 3a). G06N-020/00 refers to "computing arrangements based on specific computational models", while G16H-050/20 refers to Information and Communication Technology (ICT) "specially adapted for detecting, monitoring or modeling epidemics or pandemics for computer-aided diagnosis". For its part, G06K-009/62 relates to "methods or arrangements for pattern recognition using electronic means". A patent is usually classified in more than one code. Figure 3b depicts the IPC hierarchical structure of AI- and COVID-19-related patents. In the most aggregate section of the hierarchy, the two most frequent codes are G (Physics) and A (Human necessities), covering 95.07% and 47.89% of all patents, respectively. G06 ("Computing; Calculating or Counting"; 78.87%) and A61 ("Medical or Veterinary Science; Hygiene"; 46.48%) are the predominant codes contained in G and A, respectively. Moving down the hierarchy, we have G06N ("Computing arrangements based on specific computational models"; 56.34%) and A61B ("Diagnosis; Surgery; Identification"; 36.62%). Then, G06N-003 ("Computing arrangements based on biological models"; 30.99%) and A61B-005 ("Measuring for diagnostic purposes"; 20.42%). Finally, at the most disaggregated level, we have G06N-003/08 ("Learning methods"; 21.13%) as the most frequent code. A61B-005/00 corresponds to A61B-005, as there is no additional classification. The full descriptions of all IPC codes are available in the Supplementary Materials.

The co-occurrences between IPC codes are shown in Figure 4. According to the codes' weighted degree centrality, the three most central nodes of the network are G16H-050/20 (WDC: 310.0), G06K-009/62 (WDC: 270.0), and G06N-020/00 (WDC: 246.0), which are also the most frequent IPC codes. Although ranking third in WDC, G06N-020/00 is the most central node according to eigenvector centrality (EC: 1.0), closeness centrality (CC: 0.935484), and betweenness centrality (BC: 0.076176). Thus, it can be considered the overall most relevant node in the network. First, in WDC, G16H-050/20 ranks second in EC (0.995375) and CC (0.90625) and third in BC (0.051134). G06K-009/62, the second highest WDC, ranks eighth in EC (0.842527) and CC (0.783784) and fourth in BC (0.036958). A61B-005/00 is another central node in the network. Although ranking seventh in WDC (186.0), it is third in EC (0.965293) and CC (0.878788) and second in BC (0.053267). The network values of all network nodes are available in the Supplementary Materials.

The two-mode network represents the co-occurrence between the algorithms and application fields in patent records (Figure 5). Considering the weighted degree centrality, the three most central algorithm nodes of the network are also the most frequent: CNN (WDC: 286.0), SVM (WDC: 222.0), and RF (WDC: 162.0). Among the application field nodes, diagnosis (WDC: 354.0), prevention (WDC: 122.0), and forecast (WDC: 60.0) are the most central ones. Although forecast is not the third most frequent application, it is central for connecting to a wider range of algorithms.

The SVM is the most central node when considering eigenvector centrality (EC:1.0) and closeness centrality (CC: 0.923). This node connects to almost all other nodes in the network (the only exceptions are the nodes management and FCN). Diagnosis is the most central node (0.111) for betweenness centrality, being the shortest path to all the other nodes. All the network metrics are available in the Supplementary Materials.

The most significant connection occurs between CNN and diagnosis. They were cited together in 48 records. Of the 52 CNN algorithms, 92.31% are cited in diagnosis records. Some of these records include algorithms capable of differentiating COVID-19 from other respiratory diseases, such as Tuberculosis (IN202241041747; US2022192534), Influenza (CN111653356), and Middle East Respiratory Syndrome (IN202241005094). The second most important connection is between two algorithms, CNN and SVM. They were cited together in eleven records, one of them has a forecast application (US2022383984). The third highest connection is between SVM and diagnosis, sharing ten records. Among the 21 patent records using SVM, 47.62% are for diagnosis applications, and 33.33% are for prevention. Only two diagnosis records do not use CNN and SVM together, a detection system for COVID-19 and Influenza (IN202141055989) and an algorithm that analyzes chest CT from patients and predicts severity (IN202141037260).

Considering only connections between algorithms and application fields, after CNN–diagnosis and SVM–diagnosis, SVM–prevention is the third highest (cited together in seven records). For the connections between algorithms, after CNN-SVM, the connections between SVM-RF (ten records) and SVM-DT (eight records) are the second and third highest. Eight patent records have more than one application field. The highest co-occurrences are between diagnosis–monitoring (2), diagnosis–prognosis (2), and prevention–forecast (2).

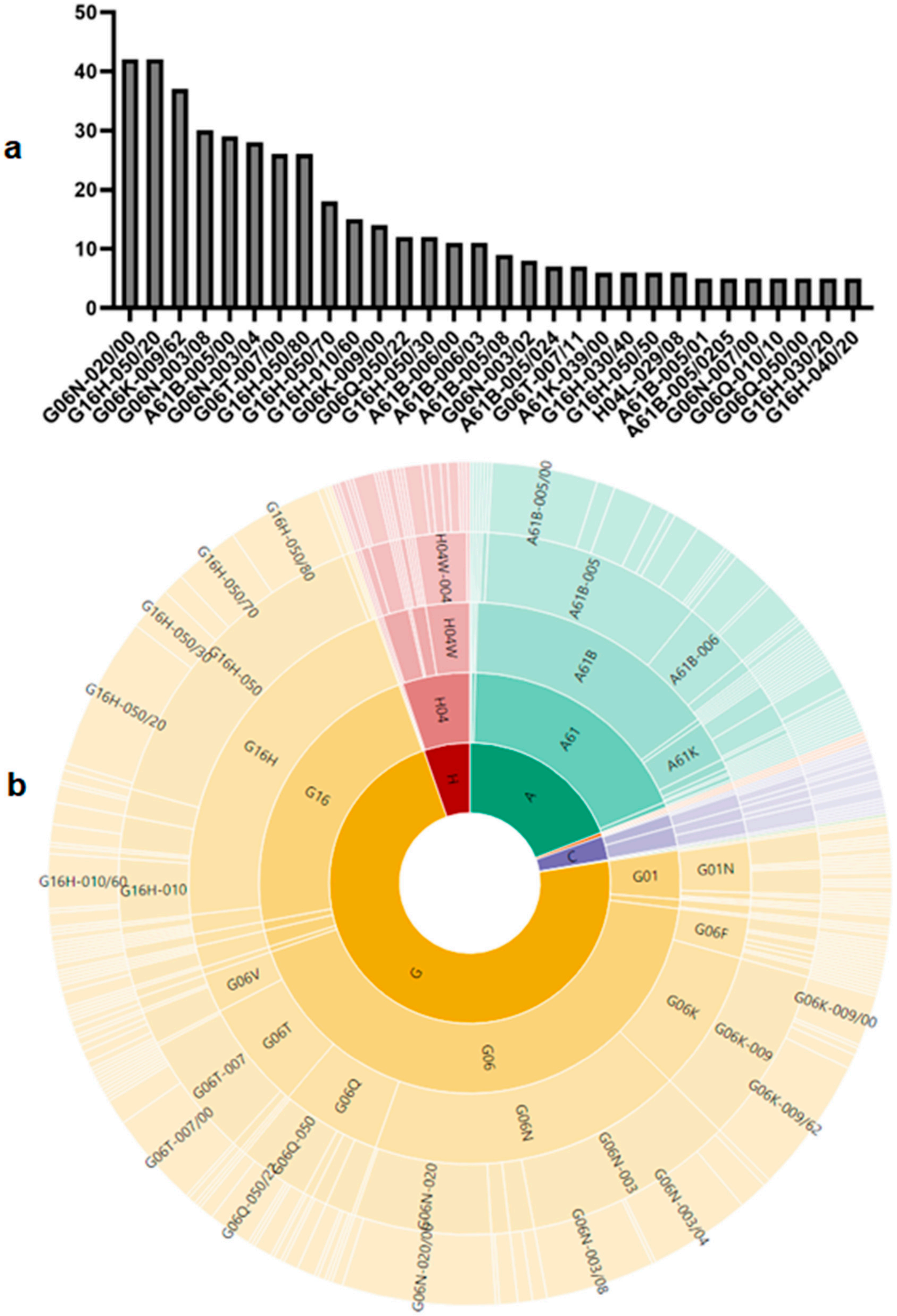

Figure 3. IPC8 analysis. (**a**) Most frequent IPC (higher or equal to five). (**b**) Sunburst of IPC (all records). It shows the hierarchical structure of the IPC codes from the most aggregate (the innermost layer) to the least aggregate (the outermost layer). The segment's size is according to their share of data.

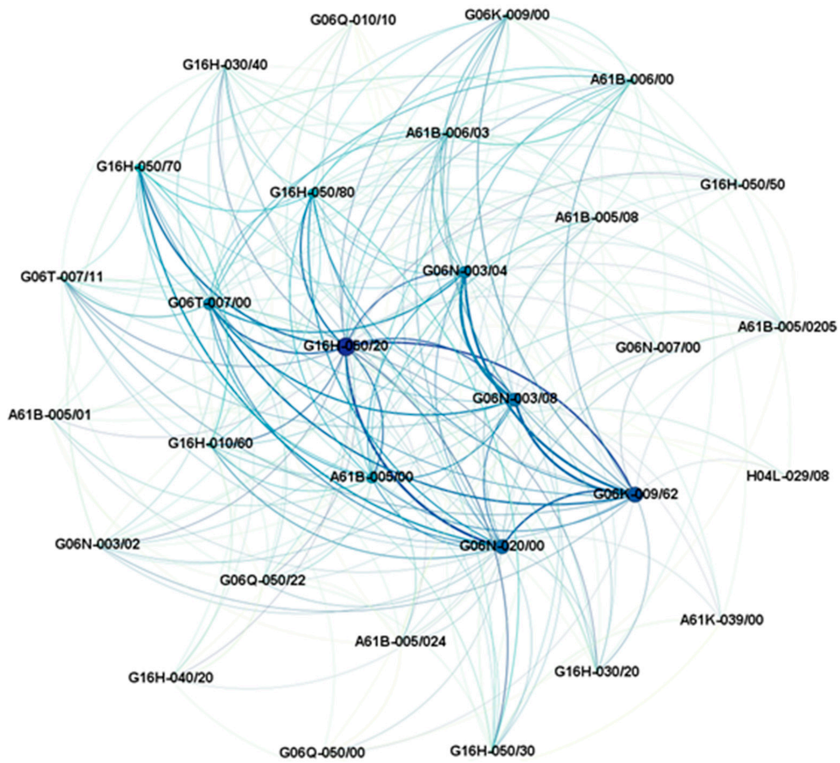

Figure 4. Network of IPC codes with a frequency higher or equal to five. The network consists of 30 nodes and 237 edges. Node sizes and colors and edges' thicknesses are given by the weighted degree centrality. The network layout was given by the Fruchterman–Reingold algorithm.

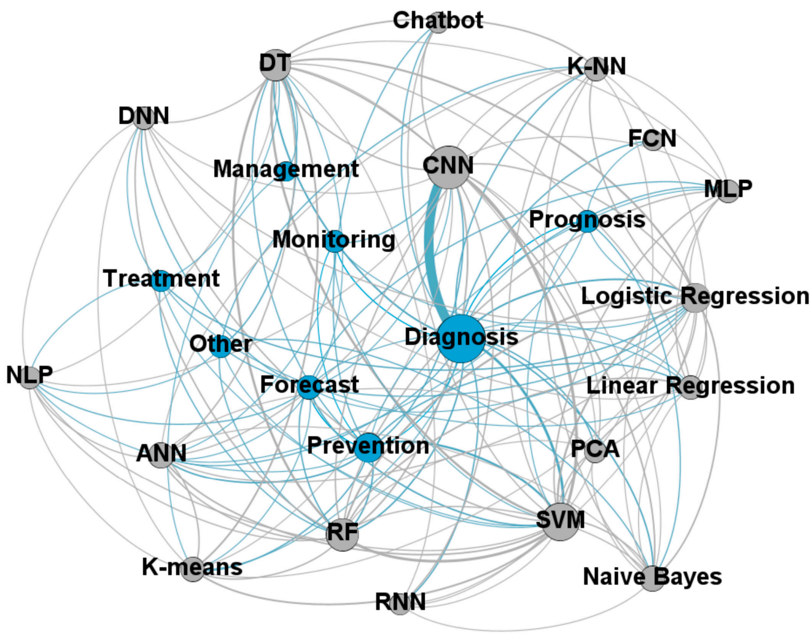

Figure 5. Two-mode network of AI-related algorithms and application fields. The network consists of 25 nodes and 144 edges. Gray nodes are algorithms (17), and blue nodes are application fields (8). Node sizes and edges' thicknesses are given by the weighted degree centrality. The networks' layout was given by the Fruchterman–Reingold algorithm. Algorithm abbreviations: Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Artificial Neural Network (ANN), K-nearest neighbors (K-NN), Natural Language Processing (NLP), Multilayer Perceptron (MLP), Deep Neural Network (DNN), Fully Convolutional Network (FCN), Principal Component Analysis (PCA), and Recurrent Neural Network (RNN).

4. Discussion

The widespread use of AI algorithms in COVID-19 patent applications is consistent with the broader trend of the increasing use of AI in healthcare research and development (R&D) over the past decade [6,30,31]. For example, the application of AI in radiology has yielded substantial advancements in diagnostic accuracy, as well as predictive analytics and treatment planning, with notable applications in mammography interpretation, cardiac function assessment, and lung cancer screening [6]. Such potential was explored during the COVID-19 pandemic, when, early in 2020, its application was expected in early detection and diagnosis, treatment monitoring, contact tracing, projection of cases and mortality, development of drugs and vaccines, reducing the workload of healthcare workers, and prevention of the disease [32].

The immense public health challenge associated with the pandemic has not only resulted in a profusion of scientific publications on the topic [33] but also can be seen in the number of patents related to it [34]. Previous studies examining patents related to COVID-19 have highlighted this increasing trend [34,35]. As for AI-related patents for COVID-19, our results show that diagnosis was the most frequent field, which is consistent with the urgent need for accurate and efficient diagnostic tools to detect COVID-19 cases [9]. This was also observed in a previous study, which found the prominence of patents for diagnosis and triage [36]. Additionally, we found that ML algorithms, such as CNN, were dominant in the diagnosis patent applications. This may be attributed to their performance in image recognition tasks since several studies have demonstrated the high accuracy of CNN-based models in diagnosing COVID-19 based on chest X-rays and CT images [37–39].

Prevention was the second most frequent field in COVID-19 patent applications, indicating the importance of proactive measures to control and prevent the spread of the virus [40]. ML algorithms, such as ANN and K-means, were the most commonly used algorithms. While ANN is a type of ML algorithm that is inspired by the structure and function of the human brain and is used for classification, regression, and prediction, K-means is a clustering algorithm used in ML for grouping data points into clusters based on their similarities [41]. Hence, both algorithms share the ability to analyze complex datasets and identify patterns and trends that inform prevention strategies [42]. For example, one of the patents in our sample (US11302448) uses ANN to generate scores that indicate levels of applicability of different digital therapeutics for COVID-19 and other diseases. Despite the predominance of patents related to diagnosis and prevention, the results show a diversity of application fields, suggesting that there is scientific, technological, and economic potential for the development and commercial exploitation of technologies that use AI to provide answers to health problems.

The prevalence of CNN, SVM, and RF algorithms in COVID-19 patent applications is consistent with their popularity in other healthcare applications as well. For instance, a recent review of AI applications in healthcare identified SVM as the most commonly used algorithm [43]. Similarly, a survey on DL in medical image analysis shows that CNN-based models have been widely used for this purpose, achieving state-of-the-art performance in several tasks [44].

The results of the bibliometric analysis added other insights into the distribution and characteristics of AI- and COVID-19-related patents. The high number of patents filed in 2021 suggests a significant interest in developing AI-based solutions to address the challenges posed by the COVID-19 pandemic, which was expected. This finding is consistent with other studies showing a surge in AI R&D in response to the pandemic [8].

India was the priority country for most patents, followed by the United States and Australia. This result could be attributed to India's large population, which has been severely affected by the pandemic [45,46], and created an urgent need for effective solutions to mitigate the impact of the virus. Moreover, India has a growing information technology industry, and its government has undertaken several initiatives to drive the adoption of AI across the country, especially in healthcare [47]. An earlier study, conducted using the

Questel Orbit database to search for patents, identified India as the country with the highest number of applications, followed by China and the USA [36].

The three most frequent IPC codes in AI- and COVID-19-related patents were related to computing arrangements based on specific computational models, information, and communication technology for detecting (code: G06N-020/00), monitoring, or modeling epidemics or pandemics (code: G16H-050/20), and methods or arrangements for pattern recognition using electronic means (code: G06K-009/62). This is consistent with the application of AI and its related algorithms in healthcare and medical research, which often involve complex data analysis and image recognition tasks [30]. Notably, the presence of G06N-003/08 ("Learning methods") as the most frequent code can be associated with the nature of part of AI algorithms, which can learn—including in an unsupervised way [4,6].

Moreover, the co-occurrence network analysis for IPC codes revealed that the most frequent codes are also the central nodes in the network, further indicating their high relevance in AI- and COVID-19-related patents. These codes are particularly useful for developing AI-based solutions for COVID-19, such as computer-aided diagnosis systems that rely on analyzing X-ray and computed tomography images (IN202141050728), predicting the spread of COVID-19 based on demographic and vaccination history data (IN202141047868) and software designed to provide personalized guidelines to individuals for improving resistance against COVID-19 (IN 202141053891).

The two-mode network between algorithms and application fields in patent records showed that CNN, SVM, and RF were the most central algorithms, while diagnosis, prevention, and forecast were the most central application fields. CNN, in particular, was cited in 48 records with diagnosis, showing its high relevance in image-based diagnostics. This is consistent with our previous findings on the most frequent AI-related algorithm and most frequent application fields, where CNN and diagnosis were the highlights. Again, the use of CNN for COVID-19 diagnosis is well established since CNN algorithms are highly effective at analyzing medical images [48], which is important since chest X-rays and CT scans are frequently used to diagnose COVID-19 [49].

As for connections between algorithms, the co-occurrence of CNN and SVM indicates the potential of using these algorithms together in COVID-19-related applications. The combination of CNN and SVM algorithms may relate to their complementary features since CNN's ability to extract relevant data from medical images can be combined with SVM's ability to classify data [50].

5. Conclusions

This study provided a comprehensive overview of the use of AI algorithms in COVID-19-related patent applications. The results suggest that AI algorithms have been widely used in diagnosis and prevention applications. DL algorithms such as CNN dominate diagnosis applications, and ML algorithms such as SVM and RF are more prevalent in prevention applications. The dominance of these algorithms is consistent with their popularity in other healthcare applications as well. The study also highlights interesting insights into the distribution and characteristics of AI and COVID-19-related patents and the co-occurrences between IPC codes and algorithms in these patents. These findings may be useful for researchers, policymakers, and industry professionals interested in developing and commercializing AI-based solutions for healthcare or public health emergencies. The study's findings underscore the pivotal role of AI algorithms in revolutionizing COVID-19 diagnosis and prevention, offering promising avenues for enhancing healthcare outcomes. In light of the growing interest and applications of AI in addressing public health challenges, future studies could delve deeper into AI algorithms for diagnosis and prevention, thereby bolstering our preparedness for future pandemics and healthcare emergencies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/make6030078/s1. Search strategies used to identify AI- and COVID-19-related publications indexed in the Web of Science Core Collection. List of included and excluded patents. Description of IPC codes. Network metrics.

Author Contributions: Conceptualization, F.M., L.A.M.B., B.P.C. and L.A.A.; methodology, F.M., L.A.M.B., B.P.C., N.C.d.S.F., C.D.P., J.A.C. and L.A.A.; validation, F.M., L.A.M.B. and B.P.C.; formal analysis, F.M. and L.A.M.B.; investigation, F.M., L.A.M.B., B.P.C., N.C.d.S.F., C.D.P., J.A.C. and L.A.A.; resources, F.M.; data curation, F.M. and L.A.M.B.; writing—original draft preparation, F.M., L.A.M.B. and B.P.C.; writing—review and editing, F.M., L.A.M.B., B.P.C., N.C.d.S.F., C.D.P., J.A.C. and L.A.A.; supervision, F.M. and L.A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Any data and materials used in the study are available on reasonable request to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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