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# AI in Medical/Medicine: Current Landscape and Future Possibilities

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**ABSTRACT** Today's medical systems have become increasingly sophisticated, dynamic, and interconnected. Although, they have simultaneously introduced new problems in terms of patient rights and privacy. Medical practices face unpredictable and random patterns due to the existence of countless uncertainties and interdependencies. Recent developments in Artificial Intelligence (AI), especially Machine Learning (ML) and Deep Learning (DL), show the potential to revolutionize healthcare by providing advanced analytical tools to handle massive amounts of medical data, including electronic health records, medical imaging, and many types of sensor data. DL algorithms can deal with increasing amounts of data provided by wearables, smart phones, and other mobile monitoring sensors pertaining to different areas of medicine. In view of the above, this paper aims to discuss the evolution of medical sciences through the use of AI. It further aims to review the recent scientific literature in order to provide an overview of the benefits and future opportunities of AI applications used in clinical practice for physicians, healthcare institutions, medical education, and bioethics.

**INDEX TERMS** artificial intelligence, big data, deep learning, health care, machine learning, medical sciences

## I. INTRODUCTION

Before the advent of mobile technology, medical devices were primarily thought of as hardware devices that were used to diagnose and treat medical conditions. These devices included prosthetics, stents, pacemakers, and other types of implants. Their usage typically required specialized training and they were used by healthcare professionals in hospitals, clinics, and other healthcare settings. The integration of Artificial Intelligence (AI) in medicine began in the early 21st century. The widespread adoption of smartphones, wearables, sensors, and the Internet of Things (IoT) has greatly accelerated the pace of its adoption. These devices and technologies have made it possible to collect, transmit, and analyze large amounts of health-related data in real-time. The data generated by these devices can be used to train machine learning algorithms, which can be integrated into a variety of medical applications [1]. Indeed, the field of medicine is entering a period of constant innovation and change. This is driven by increased data availability, as well as advances in robotics and expert systems.

AI mimics human cognitive functions. Its use is bringing a paradigm shift in healthcare, powered by the increasing availability of healthcare data and rapid progress of analytical tools [2]. This has fueled an active discussion about whether AI will eventually replace human doctors in the future. The current and mainstream opinion in academia is that AI will complement physician workflow in the future [3]. By using powerful AI techniques, such as Machine Learning (ML) and Natural Language Processing (NLP) to analyze large amounts of data, it

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is possible to uncover clinically relevant information that may not be immediately apparent. This information can be used to assist with clinical decision-making and problem-solving, potentially improving patient outcomes and overall healthcare delivery [4]. This paper is structured as follows: Section 2 discusses the reasons for transitioning to AI. Section 3 discusses the research methodologies and techniques used in literature review. Section 4 presents the results of the bibliometric analysis. Section 5 provides the discussion of these results. Finally, Section 6 outlines the main conclusions of the current research.

## II. TRANSITIONING TO AI

Medical knowledge is vast and remains constantly evolving, making it impossible for any single human being to have complete and up-to-date knowledge of every disease and its treatment. Additionally, the complex nature of many medical conditions implies that a single physician may not have enough information to make an accurate diagnosis or develop an effective treatment plan. Physicians gain a vast amount of information during medical school and are expected to continue their education throughout their career. However, it is not expected for an individual physician to have a complete understanding of all diseases and treatments. Instead, they use their training and knowledge as a foundation and rely on varied resources, such as textbooks, journals, and colleagues to stay current with the latest research and treatments.

Medical imaging plays a crucial role in the diagnosis and treatment of various diseases, however, human errors can occur during the process. It has been estimated that the average rate of errors in medical imaging ranges between 3-5% [5]. These errors include technical errors in image acquisition and interpretation, as well as communication errors between healthcare professionals. In another study, it was estimated that about 75% of diagnostic errors are related to cognition biases and physician errors [6]. Cognitive factors, such as biases, can affect a physician's ability to make accurate diagnoses and develop effective treatment plans. Some examples of cognitive biases that affect physicians include

(1) Anchoring bias: It occurs when a physician becomes fixated on an initial diagnosis or impression, even when presented with new information that contradicts it. This can lead to a delay in reaching the correct diagnosis or a failure to consider alternative diagnoses.

(2) Framing bias: When a physician over-relies on the specific way in which a question is posed or the relevant information is presented. This can lead to a biased interpretation of a patient's symptoms and to incorrect diagnosis or treatment plans.

(3) Availability bias: It occurs when a physician tends to jump to a conclusion based on a recent incident or a piece of information that is readily available, rather than considering all the available information. This can lead to a failure to consider alternative diagnoses or treatments.

(4) Satisfaction of search bias: It is also known as confirmation bias. It is a cognitive bias that occurs when individuals stop searching for new information once they have found a probable answer. This bias can lead to a failure to consider other possibilities, which negatively impacts the decision-making process. In the medical field, this bias can lead to misdiagnosis and incorrect treatment plans.

(5) Confirmation bias: It refers to the tendency of individuals to favor information that confirms their existing beliefs or hypotheses. This bias leads to a lack of critical thinking and a failure to consider alternative possibilities [7].

A research conducted at John Hopkins University in 2016 estimated that diagnostic errors are responsible for approximately 10% of all deaths in US hospitals, or roughly 250,000 deaths per year, making diagnostic errors the third leading cause of death in the United States, behind only heart disease and cancer. Most of these diagnostic errors occur in the Intensive Care Unit (ICU) setting [8]. AI has the potential to reduce diagnostic errors caused by cognitive biases because it is not affected by the same biases as human physicians. AI systems process large amounts of data, including the latest medical research, and assist physicians in making more informed decisions about diagnosis and treatment. They can be designed with the ability to learn and self-correct based on feedback, which improves their accuracy over time. Additionally, these systems can also be equipped with knowledge from various sources, such as medical journals, textbooks, and clinical practices. This may help to provide up-to-date information to assist physicians with patient care. It can be particularly useful in fields such as medicine, where new research and developments are constantly emerging [9]. Another essential factor is 'the time' a physician spends with the patient. Physician time is limited and within the allotted timeframe, a physician has to deal with the patient's preliminary medical history and documentation, including interfacing with electronic health records. There has been relatively little study of physician time as a resource for proper diagnosis [10]. The 1995 Commonwealth Fund survey found that 41% of physicians noted a decline in the amount of time spent with patients and 43% noted a decline in the amount of time spent with colleagues between 1992 and 1995 [11]. Therefore, an AI system is 'trained' through data that is generated from clinical activities, such as screening, diagnosis, treatment assignment and so on. So, it can learn similar groups of subjects, associations between subject features, and outcomes of interest to provide a patient diagnosis report within a small timeframe.

## III. METHODOLOGY

The methodology selected for this research is systematic literature review [11]. Systematic literature review is carried out in three phases: planning the review, conducting the review, and reporting the review. The literature from 1993 to 2021 was considered with the intent to understand how the role of AI in healthcare has changed over time. This time period likely reflects the advancements in various applications of AI in healthcare, such as medical imaging, natural language processing, and decision-support tools, as well as studies on the implementation and impact of AI in clinical practice. Furthermore, after the second AI winter (1987-1993), there has been a renewed interest and investment in AI research, as well as advances in technology that have made it more feasible to apply AI in healthcare. Additionally, the COVID-19 pandemic may have accelerated the implementation and adoption of AI in healthcare, as the crisis put pressure on healthcare systems to find ways to improve efficiency, reduce costs, and improve patient outcomes. Thus, to uncover these details, literature related to healthcare was gathered from two databases, namely *PubMed* and *SCOPUS.*

The entire research is conducted in three phases:

*Phase 1: Screening and Classification*

•Step 1: Identifying literature

•Step 2: Filtering results

•Step 3: Inclusion

*Phase 2: Analysis*

Section: Bibliometric analysis

*Phase 3: Discussion*

Section: Discussion

For the detailed survey of the problem, an extensive search was conducted in SCOPUS and PubMed databases with general keywords "*artificial intelligence*", "*machine learning," and "deep learning"* using Boolean operators (AND, OR, NOT (Step 1).

TABLE I
KEYWORDS

| Keywords | Time Period |
|---|---|
| Artificial Intelligence | |
| Machine Learning | 1993-2021 |
| Deep Learning | |

Then, a screening/filtering of the overall results from the extensive search in SCOPUS and PubMed databases was carried out in order to identify the studies most relevant to the research questions and of the highest quality (Step 2). Finally, the inclusion step was aimed to sele ct the documents to be analyzed in detail (Step 3).

### *A. IDENTIFYING LITERATURE*

*Identification:* In this step, the databases were explored using common keywords mostly used in the AI domain. The choice of keywords including 'AI', 'ML', and 'DL' is based on various surveys including ASRT. About, 20,000 ASRT members participated in this survey, where 74.2% respondents showed familiarity with the understanding of ML. Further, about 86.6% were familiar with the understanding of AI [12], while the keyword DL is taken by its frequency usage in AI domain.

The initial search returned #9,28,697 and #2,23,726 documents from SCOPUS and PubMed respectively, as shown in Figure 1.

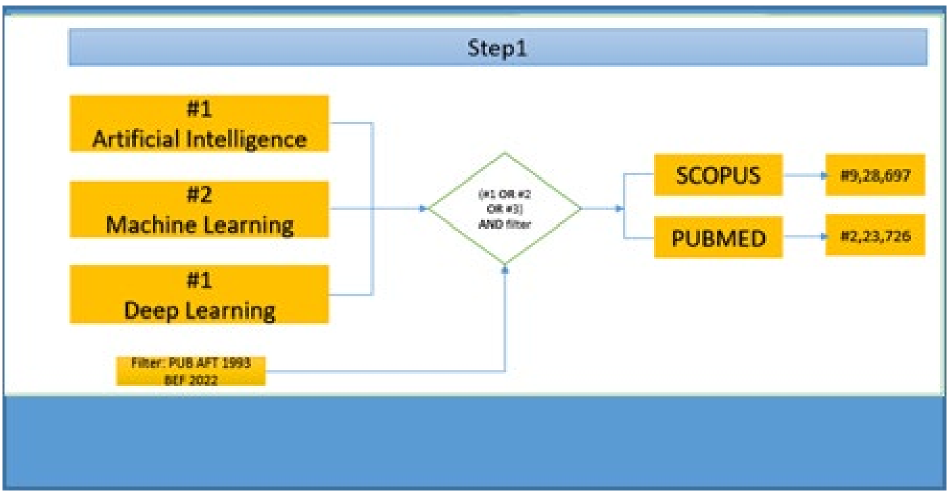



**FIGURE 1.** Identification

The initial query yielded a large result-set because it didn't include any filter criteria. Furthermore, we looked into the document type distribution in both databases. From the documents extracted from SCOPUS, it became obvious that (58.85%) were research articles and subsequently, a large percentage was that of review papers (32%), as shown in Table II.

TABLE II
SCOPUS DOCUMENT DISTRIBUTION

| Document Type | No of Document | Contribution |
|---|---|---|
| Article | 48938 | 86.04 |
| Conference Paper | 330 | 0.58 |
| Review | 5144 | 9.04 |
| Survey/ Clinical Trials | 2332 | 4.1 |
| Editorial | 133 | |
| Note | 0 | |
| Book Chapter | 0 | 0.41 |
| Book | 3 | |
| Letter | 99 | |

On the other hand, documents extracted from PubMed mainly constituted research articles (86%) and review articles (9%).

TABLE III
PUBMED DOCUMENT DISTRIBUTION

| Document Type | No of Documents | Contribution |
|---|---|---|
| Article | 27,911 | 70.27 |
| Conference Paper | 2,983 | 7.51 |
| Review | 4,868 | 12.26 |
| Editorial | 1,896 | 4.77 |
| Note | 912 | 2.3 |
| Book Chapter | 117 | |
| Book | 38 | |
| Erratum | 255 | 2.83 |
| Letter | 601 | |
| Survey | 136 | |
| Data Paper | 0 | |

After the second AI winter (1987-1993), PubMed articles grew gradually in number until 2007. Since then, article publishing rate grew rapidly until the COVID-19 pandemic struck in 2019-21, with the highest record of #12913 articles within our research domain.

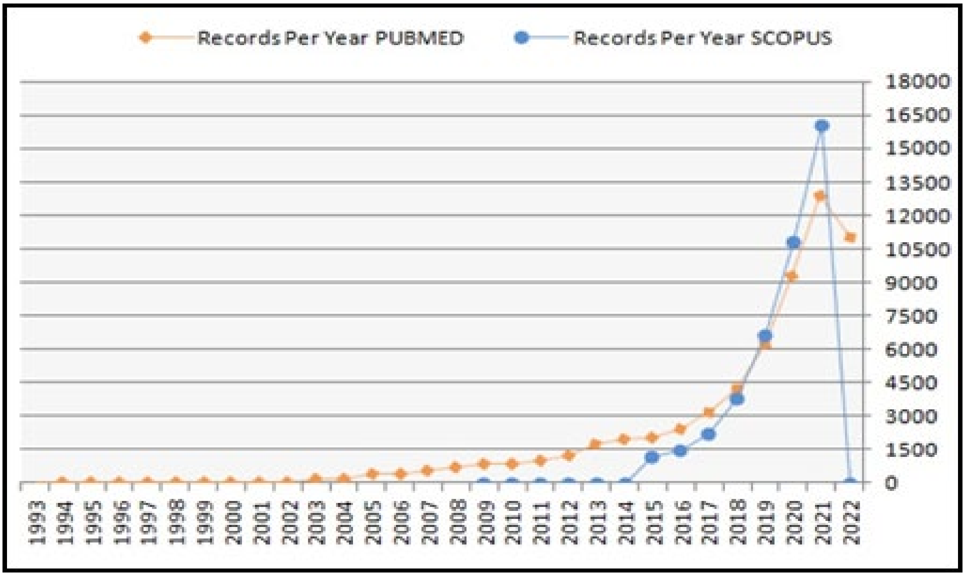



**FIGURE 2.** Year distribution

On the other hand, SCOPUS has no records of articles in the subject of interest until 2014. Since then, it has started indexing MEDLINE database and other medical databases. We found the highest record of #16000 articles in 2021, as shown in Figure 2.

### 3.2 Filtering Results

In this step, documents characterized by gold open access (documents published in journals that only publish open access) were chosen to give an overview of the topics and areas of AI in healthcare. This approach focused on studies that are freely available to the public without any restrictions. One advantage of this approach is that it allows for greater accessibility, as anyone can access and read the articles without needing to pay for a subscription or having institutional access. The search was narrowed further by applying more filters, as shown in Table iv.

TABLE IV
FILTERING

| SCOPUS |
|---|
| Open Access<br>AND SUBAREA AND [ABS-TITLE-KEY] |
| PubMed |
| Open Access<br>AND HUMANS AND SUBJAREA [ABS-TITLE-KEY] |

PubMed indexes all sorts of medical research on all species. We limited our search query to HUMANS only. After applying filters, the results decreased drastically, as shown in Table v.

TABLE V

RECORDS AFTER FILTERS

| Source | SCOPUS | PubMed |
|---|---|---|
| Results | 17,875 | 23,761 |

PubMed returned more results than SCOPUS. This is because PubMed collects data from the MEDLINE database which only contains the bibliographic data of articles related to life sciences and biomedical sciences. It includes bibliographic information from academic journals covering medicine, nursing, and pharmacy. This is one of reasons querying PubMed because it provides extensive data regarding the subject of interest. While SCOPUS, being the property of Elsevier, collects data from many sources and from many research subjects. Thus, it needed a filter to narrow down the search to the medical field only.

Table VI shows the subject areas most of the articles were categorized into.

TABLE V1
SUBJECT AREAS: SCOPUS AND PUBMED

| SCOPUS | |
|---|---|
| Medicine | Neuroscience |
| Immunology | Health Professions |
| Pharmacology | Nursing |
| Dentistry | |
| **PubMed** | |
| Medicine | Dentistry |
| Nursing | Public Health |
| Pre-clinical research | Veterinary Medicine |
| Others (Unclassified) | |

TABLE VII
MATCHED RECORDS IN SCOPUS AND PUBMED

| | |
|---|---|
| PUBMED | 23,797 |
| SCOPUS | 17,875 |
| Total Records (before matching) | 41,671 |
| Matched | 5,785 |
| Unmatched | 17,859 |
| Total Records (after matching) | 35,886 |

The subject areas in PubMed, shown in Table 6, were classified according to the data found in the Medline database. PubMed contains literature from the Medline database. On the other hand, SCOPUS contains data from many sources, including Medline. Thus, a script was created to find matching documents published in MEDLINE but indexed in both SCOPUS and PubMed using *PMID* and *DOI* identifiers as matching keys. The schema of this script is shown below in Figure 3. After running this script, it was found that 5,785 records were indexed in both databases, as shown below in Table VII.

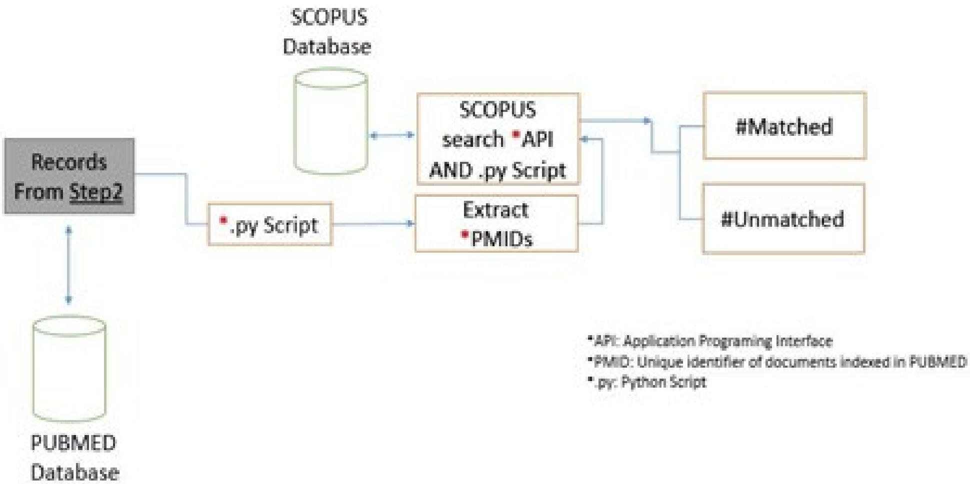



**FIGURE 3.** Matching script

### *B. INCLUSION*

In this step, documents extracted in the previous stage were considered for detailed analysis. To avoid the double analysis of matching documents (extracted from both SCOPUS and PubMed), we subtracted the records from the PubMed record list extracted in step 2.

TABLE VIII
TOTAL RECORDS

| | |
|---|---|
| PUBMED records to analyze | 23,797 – 5,785 = 17,859 |
| SCOPUS records to analyze | 17,875 |
| Total Records | 35,886 |

## IV. BIBLIOMETRIC ANALYSIS

This section presents and discusses the findings of this literature review. For bibliometric analysis, the following parameters were followed.

1. Top Influential Article: Identifying the most cited or highly regarded articles in the field.
2. Top Authors: Identifying the authors who have published the most papers or have the highest impact in the field.
3. Publications by year: Identifying trends and patterns in publications over time.
4. Collaboration among authors: Identifying patterns of collaboration among authors in the field.
5. Source Journal: Identifying the most popular journals within the field.

6. Country-wise Contribution: Identifying the countries that have the most publications or authors in the field.
7. Keyword Analysis: Identifying the most frequently used keywords in the field.

By analyzing these parameters, it became possible to get a general idea of the current state of research conducted in the field, understand the key topics and authors, and identify the trends and patterns in the literature.

### *A. TOP CITED ARTICLE*

This section lists three appendices A, B, and C. A and B list top 40 highly cited documents in both databases, namely SCOPUS and PubMed, respectively. The list is structured by Title, Research Source, TC (Total Citations), Year, Authors, and Journal Name. While, Appendix **A** lists top 20 most cited documents in the entire dataset.

From Appendix **A,** it becomes clear that the document written by Lustig, Donoho et. al and published in the journal Magnetic Resonance in Medicine in 2007 is highly cited. It has the highest citation count of 4,690. This article comprises a study to develop incoherent under-sampling schemes for better MR imaging. Furthermore, this much citations of an article suggest that AI has a great potential in the field of medical imaging. It could help in better and more accurate diagnosis using MR or CT scan images with a smaller margin of error. Even the top 2nd article listed in Appendix A and written by Kamnitsas K., Ledig C., Newcombe V.F.J., Simpson J.P., Kane A.D., Menon D.K., Rueckert D. and Glocker B. belongs to the field of medical imaging. It has received 1,907 citations since it was published in 2017. Its study lays out efficient multisampling 3D Convolutional Neural Networks (CNNs) for accurate detection of brain lesions.

Similarly, Appendix B lists top 40 articles indexed in PubMed**.** The study published in Journal of Medical Internet Research and authored by Pobiruchin M, Zowalla R and Wiesner M. in the year 2020 (during COVID-19) has been cited the most. This study unveiled temporal and geographical variations of COVID-19-related tweets. This fact allowed it to monitor the dynamic pandemic situation on a global scale for different aspects and topics, languages, regions, and even whole countries.

Appendix C contains top 20 most cited articles in the entire dataset. The list reveals that most of the frequently cited articles belong to medical imaging or radiology. Furthermore, the growth rate of citations remained slow until 2007. Only two articles had citations in thousands before 2007. An article written by Dreiseitl S. and Ohno-Machado L. in 2002, indexed in both PubMed and SCOPUS, has 1,197 citations. While, another has 1,307 citations and it was published in 2003.

Since 2007, the rate of citations was increased due to IOT, cloud computing, and Industry 4.0. A total of 17 articles out of 20 in this list have been published since 2007 and all have citations in thousands.

### *B. PUBLICATIONS BY YEAR*

This section covers the publication analysis on an yearly basis between 1993 to 2021, as shown below in Figure 4. This time period is divided into three timelines. Time period 1 showed a low growth rate of publications. The count of publications remained below thousands. The frequency of publications increased gradually after 2007, which can be verified from the top cited article section. PubMed indices increased after 2016, while rapid growth was observed in SCOPUS until 2019. The third time period or COVID-19 period [2019-2022] indicated a steady increase in publications due to pandemic, lockdowns, and other limitations. PubMed indexed 1,199 publications in 2019 but it indexed only 600 in later years. Contrary to PubMed, SCOPUS indexed highest number of publications in 2019 and 2020, as compared to previous years. However, in 2021, its indices dropped drastically and only a few publications were indexed.

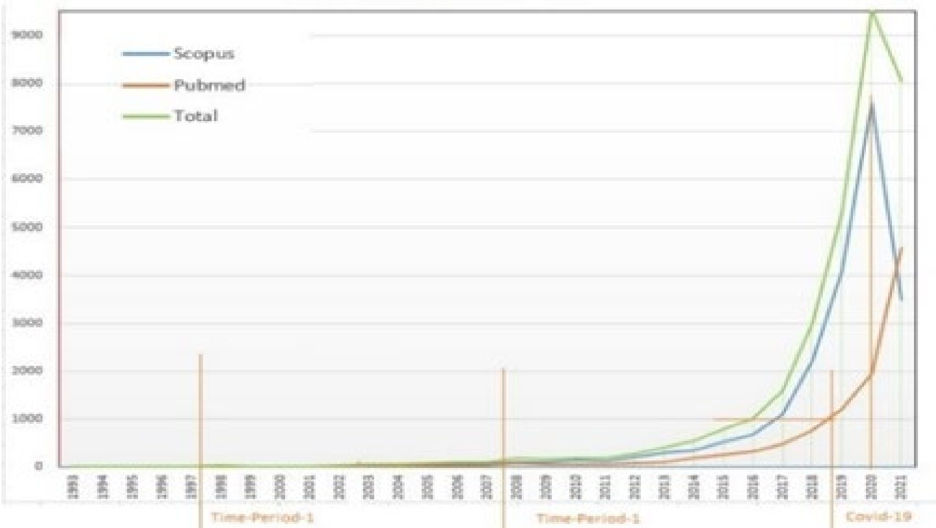



**FIGURE 4.** Publications per year

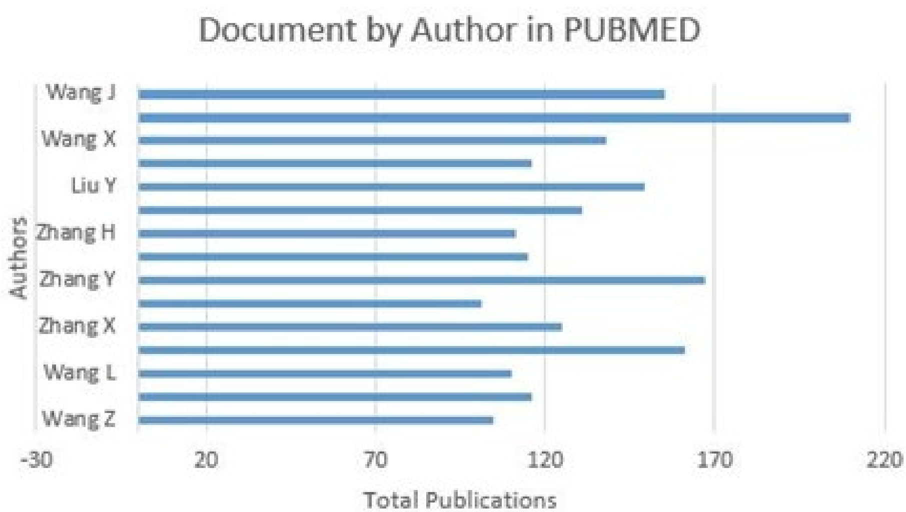



**FIGURE 5.** Top Authors in PUBMED

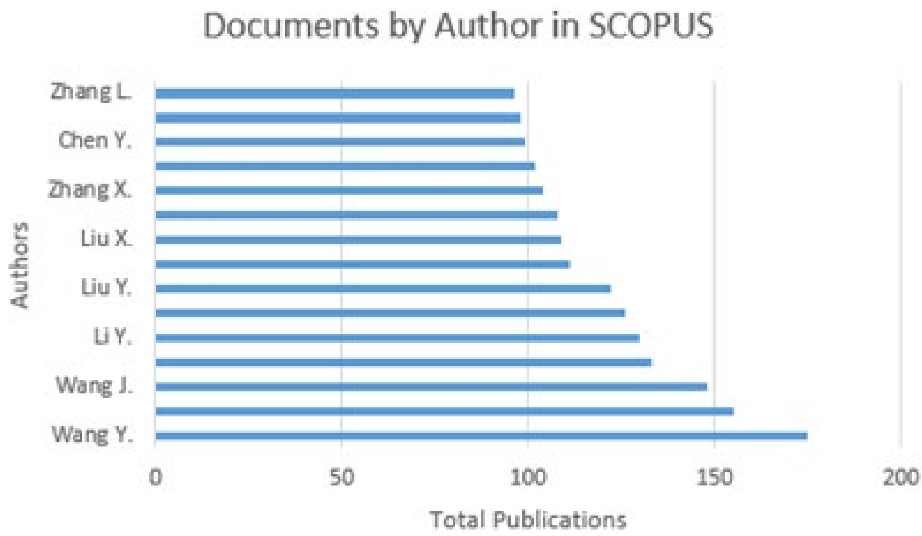



**FIGURE 6.** Top authors in SCOPUS

### *C. TOP AUTHORS*

This section highlights the analysis of Top 10 authors in the entire dataset. Figure 5 shows the top 10 authors in PubMed. Author Wang X. collaborated in 210 and Zhang Y. in 167 publications respectively which are indexed in PubMed.

Similarly, Figure 6 shows the list of top 10 authors who collaborated in publications indexed in SCOPUS. The number of collaborations of authors shown in SCOPUS is less than PubMed. SCOPUS gathers data from many sources including MEDLINE. It is not specified to medical or other biological sciences. On the other hand, PubMed gathers data related only to medical sciences. Furthermore, the publications indexed in SCOPUS under the research domain are up to the year 2020, while PubMed indices go onward as well.

### *D. AUTHOR COLLABORATION*

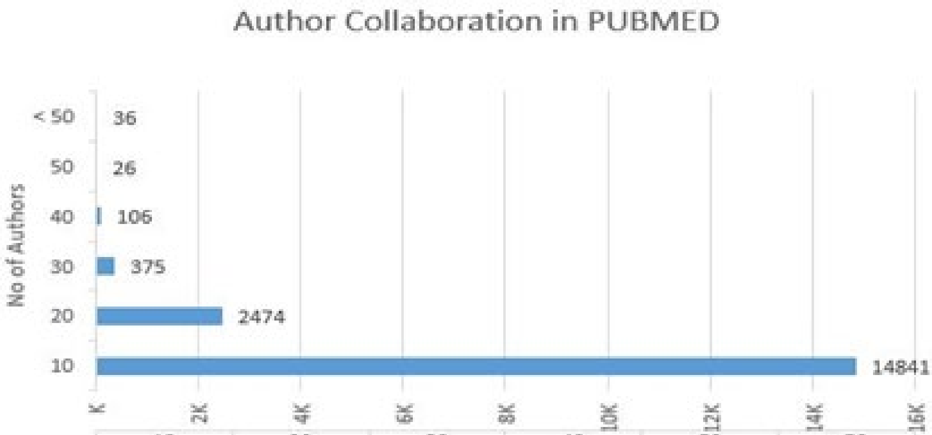
This section illuminates how many group authors collaborated per publication in both databases. It reveals that a total of 1,44,816 authors worked on publications from 1993 to 2021 in the current research domain. These included 74,226 authors in SCOPUS and 74,226 authors in PubMed, as shown in Table IX.

TABLE IX

TOTAL AUTHORS

| | |
|---|---|
| Total Authors | 1,44,816 |
| Research Source | Number of Authors |
| SCOPUS | 74,226 |
| PUBMED | 87,376 |

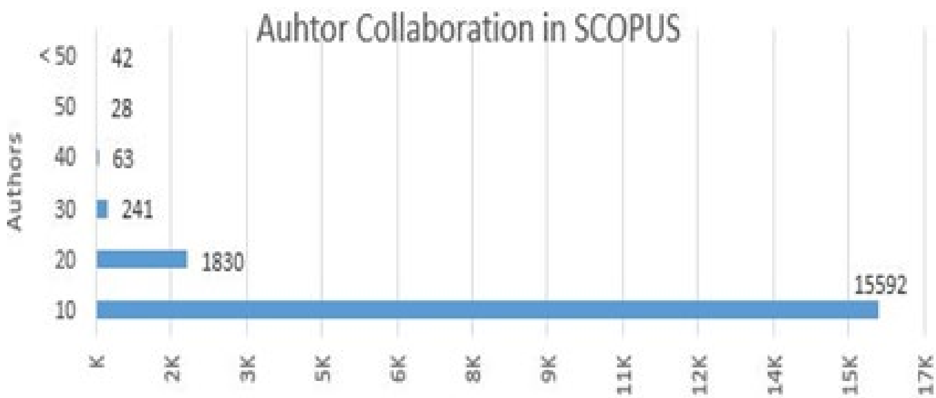
Figure 7 illustrates various ranges of authors who collaborated in various publications in PubMed. For instance, the bottom most bar shows that 14,841 publications have authors in the range 1-10. Most of the publications in PubMed lie in this range. The top most bar indicates publications having a large group of authors (more than 50).




|  | 10 | 20 | 30 | 40 | 50 | < 50 |
|---|---|---|---|---|---|---|
| TP | 14841 | 2474 | 375 | 106 | 26 | 36 |

**FIGURE 7.** Author collab in PUBMED

After analyzing further, 36 publications were found to have more than 50 authors and 4 publications had 103 authors. The number of author collaborations shown in SCOPUS is less than PubMed. SCOPUS gathers data from many sources including MEDLINE. It is not specified to medical or other biological sciences. On the other, PubMed gathers data related only to medical sciences. Furthermore, the publications indexed in SCOPUS under our research domain are up to year 2020. While PubMed indices are up to 2020 but onward as well. In SCOPUS, 15,592 documents have authors in range between 1 to 10. This is the largest collaboration group in SCOPUS as it was it PubMed as shown in Figure 8.




|  | 10 | 20 | 30 | 40 | 50 | < 50 |
|---|---|---|---|---|---|---|
| TP | 15592 | 1830 | 241 | 63 | 28 | 42 |

**FIGURE 8.** Author collab in SCOPUS

A total of 42 publications in SCOUPS had more than 50 authors. Whereas, 16 publications had hundred or more authors. Among these 16, an article written by Morato O.; Jimenez-Rojas R.; Marcos-Frutos C.; and Minguet-Arenas C. et. al and published in BMC was found to have 254 authors. Medical Informatics and Decision Making in year 2019. This article was aimed to assess the effectiveness of an intervention that could help people cease smoking and increase their nicotine abstinence rates in the long-term via ML-trained chat-bot. Average collaboration per publication in the entire dataset was 1.36, indicating 1 author per publication. Figure 9 shows combined collaboration of authors in both databases.

### *E. COUNTRY ANALYSIS*

The results of two databases are entirely different from each other, as shown in Figure 9 and Figure 10.

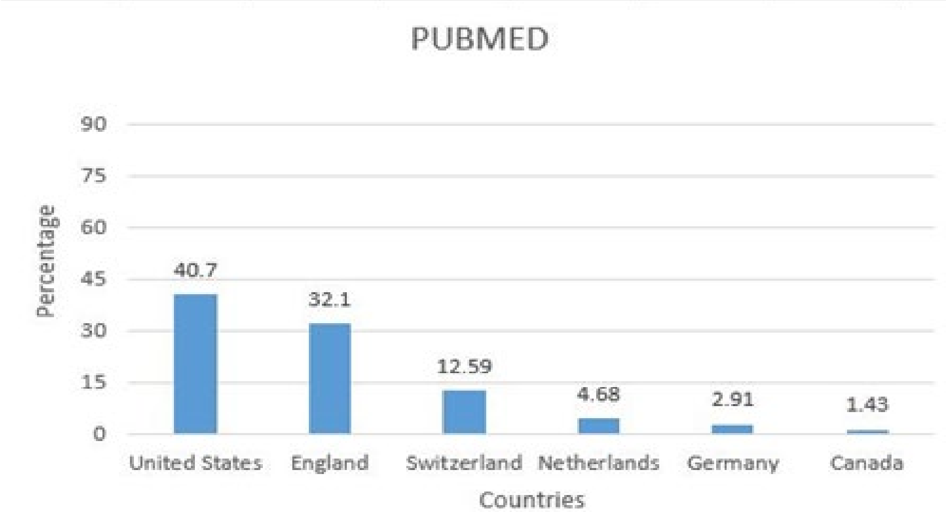



**FIGURE 9.** Country analysis

Figure 10 depicts that United States is at the top in terms of the number of publications related to AI application in medical sciences. This proves the fact that US is a leading investor in biomedical research and cutting-edge medical technology. However, at government level, it doesn't have any universal healthcare coverage system. Most of its citizens have to take/buy healthcare insurance to pay for their healthcare bill. The second leader in this domain in PubMed is England. It home to 32% of the total publications. Further, a report compiled by the Commonwealth Fund showed that England's National Health Service (NHS) tops the table of global healthcare systems.

Focusing on Europe, Switzerland is at top and is home to 12% of publications, followed by Netherlands and Germany.

Figure 11 shows that US is home to 39% of publications indexed in SCOPUS under the current research domain. China is at the second position with 14% of publications, followed by England. Combining both databases, as shown in Figure 15, United States, England, and China remain global leaders in biomedical research, followed by European countries.

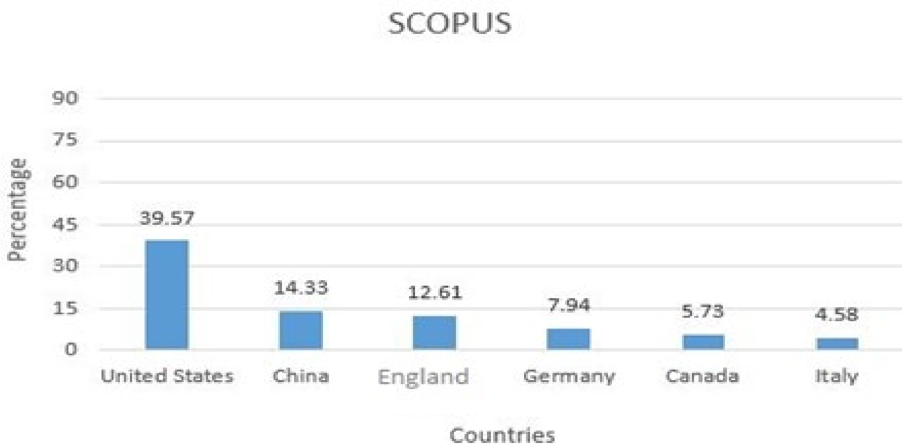



**FIGURE 10.** Country Analysis

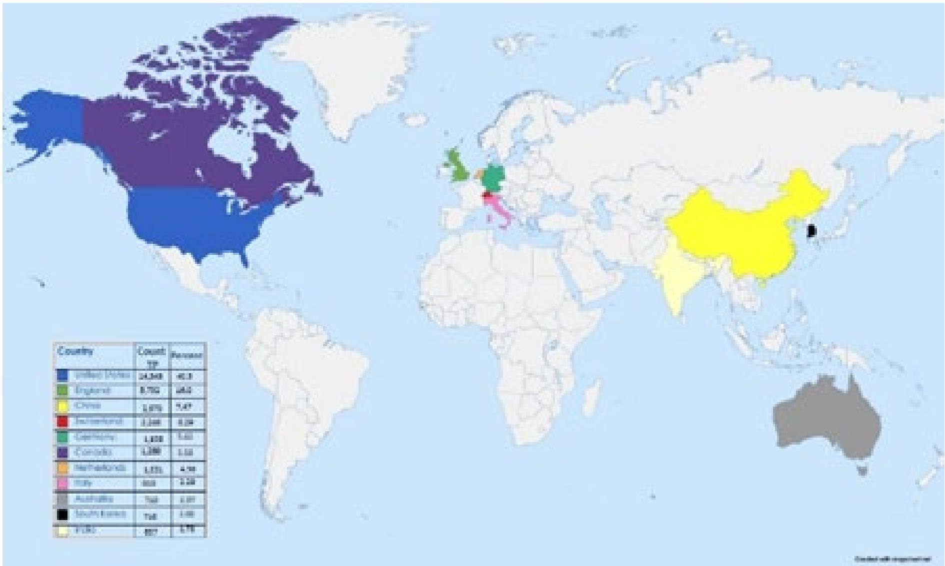


**FIGURE 11**

### *F. AFFILIATION ANALYSIS*

This section reviews author affiliations in both databases. The analysis revealed that most of the publications have one to many relationships with corresponding affiliations. Figure 12 shows affiliations in PubMed. It highlights that only the first 3 affiliations have more than 2% contribution, while the rest fall below this criterion. It further proves the point illustrated in country analysis that most of the affiliations are based in the US.

Figure 13 covers affiliations in SCOPUS. This data is consistent with the data of PubMed. It also indicates that US-based affiliations make greater contribution. For instance, Harvard Medical School, followed by Stanford University, have the highest contribution in this research domain. Figure 14 shows the percentage of Top 20 affiliations in the dataset.

The overall analysis shows that US-based affiliations contribute more than the rest of world. Most of the universities are located in the US and only few are based in China and England. Additionally, it becomes clear that China is rapidly emerging in the AI domain. An article published in Mckinsy and Company in June 2022 with the title 'The Next Frontier for AI in China' revealed that AI has the potential to add $600 billion to Chinese economy. Further, health alone may add $25 billion to the economy [13].

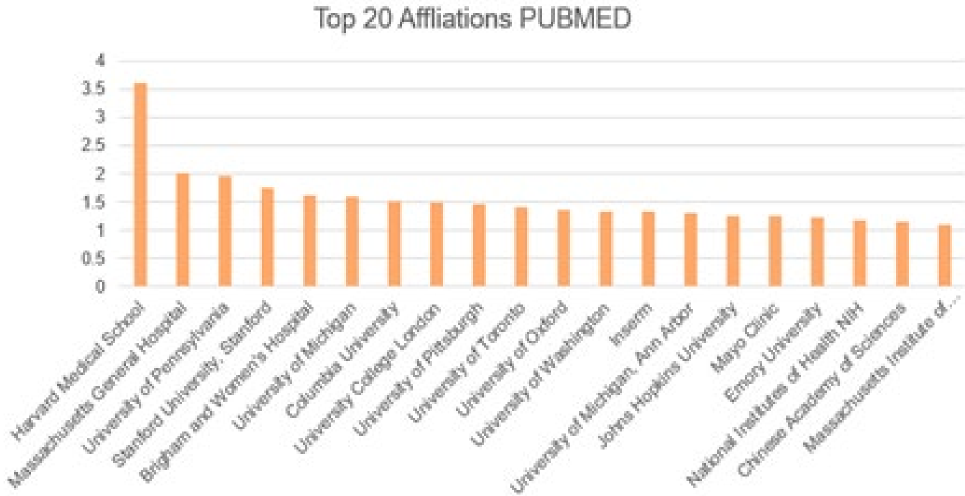



**Figure 12.** Affiliations PubMed

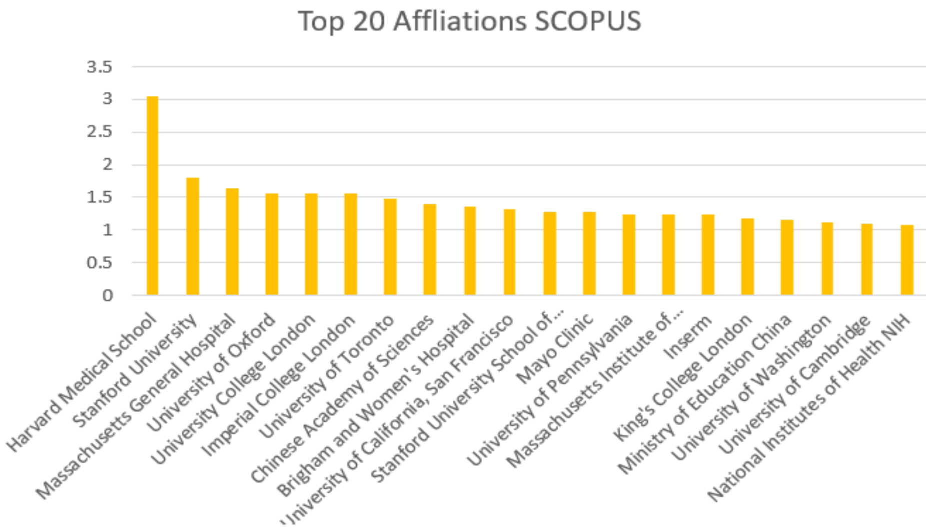



**Figure 13**. Affiliations in SCOPUS

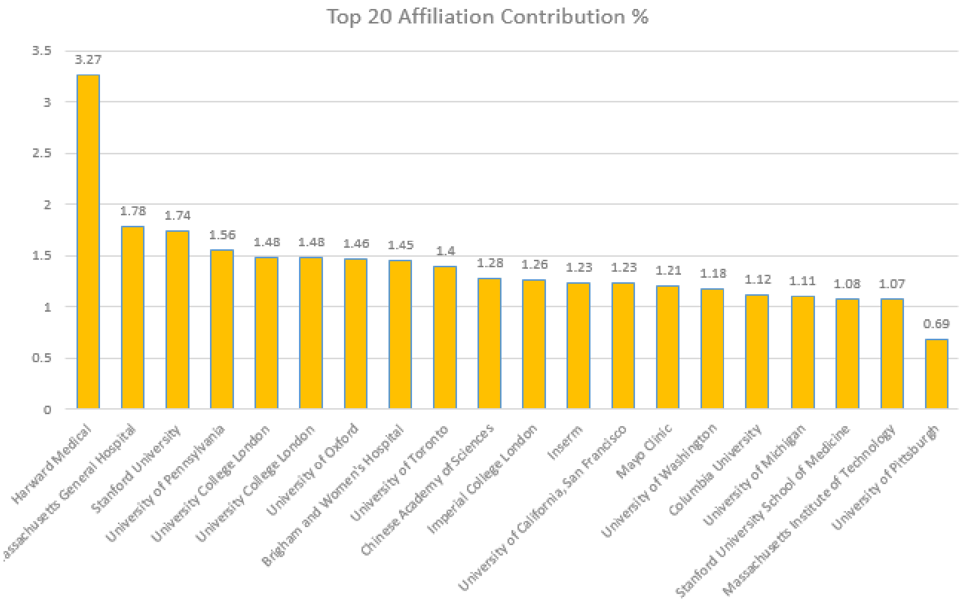



**Figure 14.** Affiliations in Whole Dataset

### *G. TOP KEYWORD ANALYSIS*

Keywords obtained from both databases were analyzed based on their frequency of occurrence in the entire dataset. A python script was used to extract keywords from the keyword section of every article. In PubMed, keywords were extracted from the keywords section, as well as from mesh heading. These mesh headings are special parameters in PubMed to classify articles. The keywords were assigned weights according to their frequency. Every/Each time a keyword occurred, its weight was incremented by 1. From both databases, 44,812 keywords were extracted. Additionally, to analyze this data graphically word-cloud was created, as shown in Figure 15. The font size of each word indicates its frequency, describing how much the keyword is indexed.


**Figure 15.** Word-Cloud

The most occurring keyword in both databases is 'humans', which indicates that most of the research papers in medical sciences are about human biology. The other most frequent words include 'artificial intelligence', 'deep learning' and 'machine learning'; the same keywords used to query the databases in the initial identification phase. The frequency of their occurrence (weight) is 6962, 5938, and 12847, respectively. Other prominent keywords related to AI include classifications, neural networks, natural language processing (NLP), image processing, convolutional neural networks (CNNs), and support vector machines (SVMs). Figure 15 also highlights the applications of AI in medical sciences. These include magnetic resonance imaging, computer simulation, computer application to medicine, biomarkers, computational tomography, computational biology, and others.

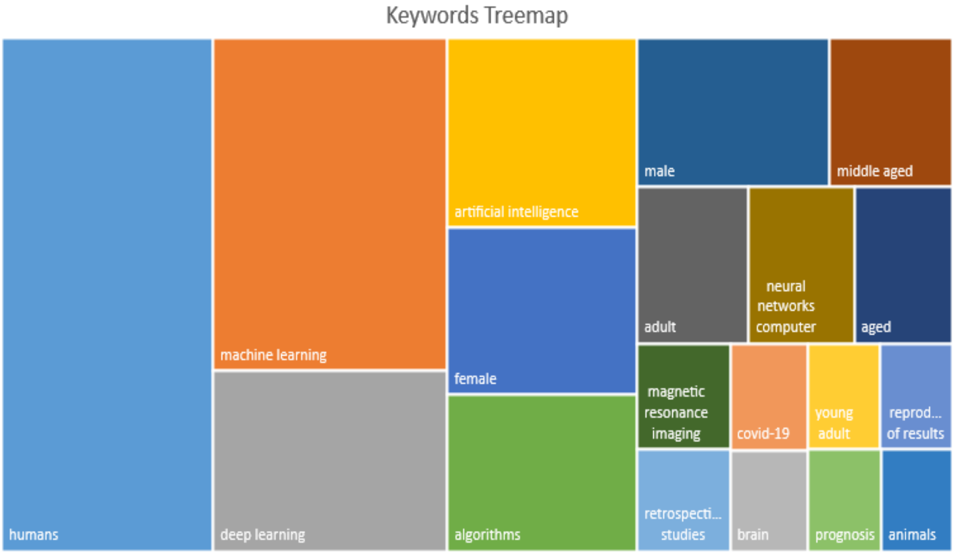



**Figure 16.** Keyword treemap

Figure 16 shows the Treemap of Top20 keywords. Box size represents the frequency of keywords. As expected, the most indexed words include 'humans', 'artificial intelligence', 'machine learning', and 'deep learning'.

## V. DISCUSSION

The analysis in the previous section highlighted that the use of AI, ML, or other related technologies has become essential in medical sciences. The publications form 1993 to 2021 prove this point. Section 2 focuses on the importance of AI in medical sciences. Medical procedures, tests, and other medical data are generally in high dimensions which could be handled via high powered data oriented computing machines or by AI technologies.

The most significant benefits of AI in medical sciences are as follows:

1. AI could handle the enormous amount of medical data and extract information related to the subject of interest in a very short period of time. It can analyze large amounts of patient data to identify patterns and predict

individual responses to treatment, allowing for more customize care.

2. Medical processes are usually slow and can be optimized using AI.
3. Medical resources could be allocated more efficiently. This is especially true for developing countries where public medical facilities have to handle a large number of patients waiting in queues for their turn.
4. It can improve treatment quality and prove to be a valuable asset in diagnostics and treatments.

About thirty-five thousand publications were found to be indexed in SCOPUS and PubMed (1993-2021) in which the use of AI or AI-related technology or AI algorithms were mentioned for various medical problems. The second important piece of information we obtained from this analysis is regarding authors and affiliations. Most of the authors have a one to many (1:M) relationship with publications and same case affiliations. It proves that the scientific community is not exploring only one domain but it is simultaneously exploring other domains as well. USA, China, and European countries are leading this domain and this should not come as a surprise. They have invested more than any other country in this domain. Indeed, US and China are competing hard to gain superiority in the AI sector. China has clearly stated its ambitions to become AI leader by 2030 [14].

### *A. EMERGING NEED OF AI AND ML IN MEDICAL SCIENCES*

Before 2007, as shown in Figure **6,** research in the medical domain regarding the use of AI for problem solving remained scarce. After 2007, scientific community realized its potential. Most of the publications indexed in SCOPUS and PubMed regarding AI application are dated after 2019. Indeed, the publication rate exploded during COVID-19. People needed to find a solution to tackle the current pandemic situation. So, they shifted to AI to solve this problem because it can handle high dimensional data and provide accurate results within a small timeframe. Hence, COVID-19 remains one of reasons that brought forth the need for AI among the scientific community. This is because conventional medical processes proved to be very slow and could get very expensive in such situations due to a lack of resources.

Moreover, the article list obtained in the above section showed that most of the publications belong to the fields of medical imaging or radiology. So, imaging is another important factor that employs AI and ML technologies. It has been estimated that about 75% of diagnostic errors are related to cognitive factors affecting the physicians [15]. Machine learning and other AI systems have the potential to be less susceptible to certain cognitive biases that can affect human decision-making, such as the availability bias and the framing bias. They can also help to improve the efficiency of routine tasks, such as image analysis and routine data entry tasks, allowing healthcare professionals to focus on more complex tasks that require human expertise. AI can also be equipped with learning and self-correcting abilities to improve its accuracy based on feedback.

Table X summarizes the main areas in medical sciences, their respective key objectives, and the main AI/ML applications.

TABLE X

MAIN AREAS

| Main Areas | AI/ML Applications |
|---|---|
| Improve Diagnositcs | AL helps to structure, normalize, and analyze health data to make better and quicker decisions, such as precision diagnosis, using genomic sequencing, early-state cancer detection, or advanced cardiac visualization with custom machine learning models. |
| Accelerate Drug Discovery | ML suitable rapid experimentation for drug discovery and also enable smart manufacturing and post-market surveillance to detect adverse events. |
| Modernize Care Infrastruc-Ture | The health industry is complex with a lot of manual, paper-based processes and health records. Using document classification, natural language understanding, and speech-to-text technologies, machine learning can simplify and automate processes to help improve efficiency, reduce hospital waste, and decrease physician burnout. |
| Manage Population Health | Machine learning tools provide a chronological view of medical events to help healthcare organizations analyze population health trends and outcomes. Biopharma organizations can analyze large-scale population genomic studies |

## *B. CONCLUSION*

The main purpose of this research was to provide a literature review on AI/ML/DL application in the field of medical sciences for the years 1993-2021. During this period, various ups and downs occurred in research. Electronic Health Records (EHR) have accelerated medical research. AI has a great potential in the medical field and its recent advancements prove this point. However, there are some obstacles AI has to overcome before it can be fully implemented. The first and foremost is that the use of AI must be accepted by users and patients in the medical domain. People normally don't trust machines or automated applications for the purpose of treatment or diagnosis. Furthermore, society has become increasingly accustomed to IT-related technical errors or failures. Such faults are likely to be deemed unacceptable in medical and health applications. This raises another problem: what if a system misdiagnoses a disease or suggests incorrect treatment, then who should be medically blamed for the wrong prediction?

Another major challenge is determining the accuracy of predictions for diagnosis and treatment and other Expert Systems (ES). Opinions from physicians having different specialties or subspecialties often contradict each other in a single case. There is no standard or protocol in medical sciences that could reflect expert opinion. The majority of opinions are based on the outcomes of previous cases.

The literature available on any subject today is distributed widely and to cover it all could be challenging or even impossible. Therefore, only two databases were selected and a systematic review mechanism was implemented only on the relevant data. The data was inconsistent because both databases implemented different data formats. Therefore, we filtered it down using programing and other text parsing technologies in order to make it consistent and integrated as a single dataset. Inconsistent data could prove very harmful during research. It may yield inaccurate and ambiguous results. There are other data documents with restricted access, as well as other indexing databases, that could be integrated similarly for future research.

There was almost no research conducted before AI winter (before 1993) or it wasn't indexed in any database. Afterwards, slow growth was observed in this domain until 2007. Then, the pace of research accelerated and the highest number of publications were indexed between 2019 and 2021. By looking at these patterns, these ups and downs some important questions arise: would there be similar ups and downs in the future? would there be another AI winter?

### Author Contribution

**Qamar Abbas:** sole author

### Conflict of Interest

The authors of the manuscript have no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

### Data Availability Statement

Data supporting the findings of this study will be made available by the corresponding author upon request.

### Funding Details

No funding has been received for this research.

### Generative AI Disclosure Statement

The authors did not use any type of generative artificial intelligence software for this research.

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# APPENDIX A

## Top 40 Highly Cited Documents in SCOPUS

| Counter | Title | Research Source | Total Citations | Year | Authors | Source Title |
|---|---|---|---|---|---|---|
| 1 | Sparse MRI: The application of compressed sensing for rapid MR imaging | SCOPUS | 4690 | 2007 | Lustig M.; Donoho D.; Pauly J.M. | Magnetic Resonance in Medicine |
| 2 | Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation | PubMed AND SCOPUS | 1907 | 2017 | Kamnitsas K.; Ledig C.; Newcombe V.F.J.; Simpson J.P.; Kane A.D.; Menon D.K.; Rueckert D.; Glocker B. | Medical Image Analysis |
| 3 | The evaluation of tumor-infiltrating lymphocytes (TILS) in breast cancer: Recommendations by an International TILS Working Group 2014 | SCOPUS | 1560 | 2015 | Salgado R.; Denkert C.; Demaria S.; Sirtaine N.; Klauschen F.; Pruneri G.; Wienert S.; Van den Eynden G.; Baehner F.L.; Penault-Llorca F.; Perez E.A.; Thompson E.A.; Symmans W.F.; | Annals of Oncology |
| 4 | Optimizing taxonomic classification of marker-gene amplicon sequences with QIIME 2's q2-feature-classifier plugin | SCOPUS | 1540 | 2018 | Bokulich N.A.; Kaehler B.D.; Rideout J.R.; Dillon M.; Bolyen E.; Knight R.; Huttley G.A.; Gregory Caporaso J. | Microbiome |
| 5 | Predicting the sequence specificities of DNA- and RNA-binding proteins by deep learning | SCOPUS | 1396 | 2015 | Alipanahi B.; Delong A.; Weirauch M.T.; Frey B.J. | Nature Biotechnology |
| 6 | Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer | PubMed AND SCOPUS | 1339 | 2017 | Bejnordi B.E.; Veta M.; Van Diest P.J.; Van Ginneken B.; Karssemeijer N.; Litjens G.; Van Der Laak J.A.W.M.; Hermsen M.; Manson Q.F.; Balkenhol M.; Geessink O.; Stathonikos N.; Van Dijk M.C.R.F.; Bult Venâncio R. | JAMA - Journal of the American Medical Association |
| 7 | Convolutional neural networks: | SCOPUS | 1317 | 2018 | Yamashita R.; Nishio M.; Do R.K.G.; | Insights into Imaging |

| Counter | Title | Research Source | Total Citations | Year | Authors | Source Title |
|---|---|---|---|---|---|---|
| | an overview and application in radiology | | | | Togashi K. | |
| 8 | Learning to control a brain-machine interface for reaching and grasping by primates | SCOPUS | 1307 | 2003 | Carmena J.M.; Lebedev M.A.; Crist R.E.; O'Doherty J.E.; Santucci D.M.; Dimitrov D.F.; Patil P.G.; Henriquez C.S.; Nicolelis M.A.L. | PLoS Biology |
| 9 | Predicting small-molecule pharmacokinetic and toxicity properties using graph-based signatures | SCOPUS | 1282 | 2015 | Pires D.E.V.; Blundell T.L.; Ascher D.B. | Journal of Medicinal Chemistry |
| 10 | Automated detection of COVID-19 cases using deep neural networks with X-ray images | PubMed AND SCOPUS | 1243 | 2020 | Ozturk T.; Talo M.; Yildirim E.A.; Baloglu U.B.; Yildirim O.; Rajendra Acharya U. | Computers in Biology and Medicine |
| 11 | Logistic regression and artificial neural network classification models: A methodology review | PubMed AND SCOPUS | 1197 | 2002 | Dreiseitl S.; Ohno-Machado L. | Journal of Biomedical Informatics |
| 12 | Large-scale mapping and validation of Escherichia coli transcriptional regulation from a compendium of expression profiles | SCOPUS | 1102 | 2007 | Faith J.J.; Hayete B.; Thaden J.T.; Mogno I.; Wierzbowski J.; Cottarel G.; Kasif S.; Collins J.J.; Gardner T.S. | PLoS Biology |
| 13 | Artificial intelligence in healthcare: Past, present and future | PubMed AND SCOPUS | 1100 | 2017 | Jiang F.; Jiang Y.; Zhi H.; Dong Y.; Li H.; Ma S.; Wang Y.; Dong Q.; Shen H.; Wang Y. | Stroke and Vascular Neurology |
| 14 | Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks | PubMed AND SCOPUS | 1084 | 2020 | Apostolopoulos I.D.; Mpesiana T.A. | Physical and Engineering Sciences in Medicine |
| 15 | Online mental health services in China during the COVID-19 | SCOPUS | 1052 | 2020 | Liu S.; Yang L.; Zhang C.; Xiang Y.-T.; Liu Z.; Hu S.; Zhang B. | The Lancet Psychiatry |

| Counter | Title | Research Source | Total Citations | Year | Authors | Source Title |
|---|---|---|---|---|---|---|
| | outbreak | | | | | |
| 16 | Deep learning with convolutional neural networks for EEG decoding and visualization | SCOPUS | 1017 | 2017 | Schirrmeister R.T.; Springenberg J.T.; Fiederer L.D.J.; Glasstetter M.; Eggensperger K.; Tangermann M.; Hutter F.; Burgard W.; Ball T. | Human Brain Mapping |
| 17 | Deep Learning for Health Informatics | PubMed AND SCOPUS | 966 | 2017 | Ravi D.; Wong C.; Deligianni F.; Berthelot M.; Andreu-Perez J.; Lo B.; Yang G.-Z. | IEEE Journal of Biomedical and Health Informatics |
| 18 | Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes | SCOPUS | 948 | 2017 | Ting D.S.W.; Cheung C.Y.-L.; Lim G.; Tan G.S.W.; Quang N.D.; Gan A.; Hamzah H.; | JAMA - Journal of the American Medical Association |
| 19 | Scalable and accurate deep learning with electronic health records | SCOPUS | 943 | 2018 | Rajkomar A.; Oren E.; Chen K.; Dai A.M.; Hajaj N.; Hardt M.; Liu P.J.; Liu X.; Marcus J.; | npj Digital Medicine |
| 20 | The impact of covid-19 epidemic declaration on psychological consequences: A study on active weibo users | PubMed AND SCOPUS | 891 | 2020 | Li S.; Wang Y.; Xue J.; Zhao N.; Zhu T. | International Journal of Environmental Research and Public Health |
| 21 | Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions | SCOPUS | 807 | 2020 | Yang Z.; Zeng Z.; Wang K.; Wong S.-S.; Liang W.; Zanin M.; Liu P.; Cao X.; Gao Z.; Mai Z.; Liang J.; Liu X.; Li S.; Li Y.; Ye F.; Guan W.; Yang Y.; Li F.; Luo S.; Xie Y.; Liu B.; Wang Z.; Zhang S.; Wang Y.; Zhong N.; He J. | Journal of Thoracic Disease |
| 22 | REVEL: An Ensemble Method for Predicting the Pathogenicity of Rare Missense Variants | SCOPUS | 804 | 2016 | Ioannidis N.M.; Rothstein J.H.; Pejaver V.; Middha S.; McDonnell S.K.; | American Journal of Human Genetics |
| 23 | An overview of | SCOPUS | 788 | 2019 | Lundervold A.S.; | Zeitschrift fur |

| Counter | Title | Research Source | Total Citations | Year | Authors | Source Title |
|---|---|---|---|---|---|---|
| | deep learning in medical imaging focusing on MRI | | | | Lundervold A. | Medizinische Physik |
| 24 | CellProfiler 3.0: Next-generation image processing for biology | SCOPUS | 785 | 2018 | McQuin C.; Goodman A.; Chernyshev V.; Kamentsky L.; Cimini B.A.; Karhohs K.W.; Doan M.; Ding L.; Rafelski S.M.; Thirstrup D.; Wiegraebe W.; Singh S.; Becker T.; Caicedo J.C.; Carpenter A.E. | PLoS Biology |
| 25 | Deep learning for computational biology | SCOPUS | 759 | 2016 | Angermueller C.; Pärnamaa T.; Parts L.; Stegle O. | Molecular Systems Biology |
| 26 | The rise of deep learning in drug discovery | SCOPUS | 730 | 2018 | Chen H.; Engkvist O.; Wang Y.; Olivecrona M.; Blaschke T. | Drug Discovery Today |
| 27 | COVID-19: combining antiviral and anti-inflammatory treatments | SCOPUS | 716 | 2020 | Stebbing J.; Phelan A.; Griffin I.; Tucker C.; Oechsle O.; Smith D.; Richardson P. | The Lancet Infectious Diseases |
| 28 | Applications of machine learning in cancer prediction and prognosis | SCOPUS | 702 | 2006 | Cruz J.A.; Wishart D.S. | Cancer Informatics |
| 29 | A simple algorithm for identifying negated findings and diseases in discharge summaries | SCOPUS | 697 | 2001 | Chapman W.W.; Bridewell W.; Hanbury P.; Cooper G.F.; Buchanan B.G. | Journal of Biomedical Informatics |
| 30 | 2010 i2b2/VA challenge on concepts, assertions, and relations in clinical text | SCOPUS | 674 | 2011 | Uzuner Ö.; South B.R.; Shen S.; DuVall S.L. | Journal of the American Medical Informatics Association |
| 31 | Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases | SCOPUS | 660 | 2016 | Janowczyk A.; Madabhushi A. | Journal of Pathology Informatics |
| 32 | Recent Progress in Electronic Skin | SCOPUS | 640 | 2015 | Wang X.; Dong L.; Zhang H.; Yu R.; Pan C.; Wang Z.L. | Advanced Science |
| 33 | Analysis and prediction of leucine-rich nuclear export signals | SCOPUS | 630 | 2004 | La Cour T.; Kiemer L.; Mølgaard A.; Gupta R.; Skriver K.; Brunak S. | Protein Engineering, Design and Selection |

| Counter | Title | Research Source | Total Citations | Year | Authors | Source Title |
|---|---|---|---|---|---|---|
| 34 | A new map of global urban extent from MODIS satellite data | SCOPUS | 616 | 2009 | Schneider A.; Friedl M.A.; Potere D. | Environmental Research Letters |
| 35 | Translational biomarker discovery in clinical metabolomics: An introductory tutorial | SCOPUS | 613 | 2013 | Xia J.; Broadhurst D.I.; Wilson M.; Wishart D.S. | Metabolomics |
| 36 | Man against Machine: Diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists | PubMed AND SCOPUS | 600 | 2018 | Haenssle H.A.; Fink C.; Schneiderbauer R.; Toberer F.; Buhl T.; Blum A.; Kalloo A.; Ben Hadj Hassen A.; Thomas L.; Enk A. | Annals of Oncology |
| 37 | Artificial Intelligence (AI) applications for COVID-19 pandemic | SCOPUS | 597 | 2020 | Vaishya R.; Javaid M.; Khan I.H.; Haleem A. | Diabetes and Metabolic Syndrome: Clinical Research and Reviews |
| 38 | A Deep Cascade of Convolutional Neural Networks for Dynamic MR Image Reconstruction | SCOPUS | 575 | 2018 | Schlemper J.; Caballero J.; Hajnal J.V.; Price A.N.; Rueckert D. | IEEE Transactions on Medical Imaging |
| 39 | Bio2RDF: Towards a mashup to build bioinformatics knowledge systems | SCOPUS | 570 | 2008 | Belleau F.; Nolin M.-A.; Tourigny N.; Rigault P.; Morissette J. | Journal of Biomedical Informatics |
| 40 | CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images | SCOPUS | 566 | 2020 | Khan A.I.; Shah J.L.; Bhat M.M. | Computer Methods and Programs in Biomedicine |

## APPENDIX B

Top 40 Highly Cited Documents in PubMed

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| 1 | Temporal and Location Variations, and Link | 2,789 | PubMed | 2020 | Pobiruchin M, Zowalla R, | J Med Internet |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | Categories for the Dissemination of COVID-19-Related Information on Twitter During the SARS-CoV-2 Outbreak in Europe: Infoveillance Study | | | | Wiesner M. | Res |
| 2 | Correlation of Chest CT and RT-PCR Testing for Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases | 2,525 | PubMed | 2020 | Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, Tao Q, Sun Z, Xia L. | Radiolog y |
| 3 | Dermatologist-level classification of skin cancer with deep neural networks | 1,998 | PubMed | 2017 | Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S. | Nature |
| 4 | The interaction of domain knowledge and linguistic structure in natural language processing: interpreting hypernymic propositions in biomedical text | 1,787 | PubMed | 2003 | Rindflesch TC, Fiszman M. | J Biomed Inform |
| 5 | Deep convolutional neural network for segmentation of knee joint anatomy | 1,477 | PubMed | 2018 | Zhou Z, Zhao G, Kijowski R, Liu F. | Magn Reson Med |
| 6 | Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features | 1,477 | PubMed | 2019 | Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, Duncan JS, Chapiro J, Letzen B. | Eur Radiol |
| 7 | Genetic effects on gene expression across human tissues | 1,468 | PubMed | 2017 | GTEx Consortium; Laboratory, Data Analysis &Coordinating Center (LDACC),et.al | Nature |
| 8 | Early prediction of level-of-care requirements in patients with COVID-19 | 1,324 | PubMed | 2020 | Hao B, Sotudian S, Wang T, Xu T, Hu Y, Gaitanidis A, Breen K, Velmahos GC, Paschalidis IC. | Elife |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| 9 | Integrated problem-based learning versus lectures: a path analysis modelling of the relationships between educational context and learning approaches | 1,193 | PubMed | 2018 | Gustin MP, Abbiati M, Bonvin R, Gerbase MW, Baroffio A. | Med Educ Online |
| 10 | SARS-CoV-2 Receptor ACE2 Is an Interferon-Stimulated Gene in Human Airway Epithelial Cells and Is Detected in Specific Cell Subsets across Tissues | 1,104 | PubMed | 2020 | Ziegler CGK, Allon SJ, Nyquist SK, Mbano IM, Miao VN, Tzouanas CN, Cao Y, Yousif AS, Bals J, Hauser BM, Feldman J, et.al | Cell |
| 11 | Ribosome profiling of mouse embryonic stem cells reveals the complexity and dynamics of mammalian proteomes | 1,075 | PubMed | 2011 | Ingolia NT, Lareau LF, Weissman JS. | Cell |
| 12 | White Matter Connectome Edge Density in Children with Autism Spectrum Disorders: Potential Imaging Biomarkers Using Machine-Learning Models | 1,070 | PubMed | 2019 | Payabvash S, Palacios EM, Owen JP, Wang MB, Tavassoli T, Gerdes M, Brandes-Aitken A, Cuneo D, Marco EJ, Mukherjee P. | Brain Connect |
| 13 | Prediction of Neurological Outcomes in Out-of-hospital Cardiac Arrest Survivors Immediately after Return of Spontaneous Circulation: Ensemble Technique with Four Machine Learning Models | 1,037 | PubMed | 2021 | Heo JH, Kim T, Shin J, Suh GJ, Kim J, Jung YS, Park SM, Kim S; For SNU CARE investigators. | J Korean Med Sci |
| 14 | GENCODE reference annotation for the human and mouse genomes | 1,034 | PubMed | 2019 | Frankish A, Diekhans M, Ferreira AM, Johnson R, Jungreis I, Loveland J, Mudge JM, Sisu C, Wright J, Armstrong J, Barnes I, et.al | Nucleic Acids Res |
| 15 | CADD: predicting the deleteriousness of variants throughout the human genome | 1,034 | PubMed | 2019 | Rentzsch P, Witten D, Cooper GM, Shendure J, | Nucleic Acids Res |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | | | | | Kircher M. | |
| 16 | White matter microstructure across the adult lifespan: A mixed longitudinal and cross-sectional study using advanced diffusion models and brain-age prediction | 1,032 | PubMed | 2021 | Beck D, de Lange AG, Maximov II, Richard G, Andreassen OA, Nordvik JE, Westlye LT. | Neuroimage |
| 17 | Changes in disease burden in Poland between 1990-2017 in comparison with other Central European countries: A systematic analysis for the Global Burden of Disease Study 2017 | 1,028 | PubMed | 2020 | GaÅ„czak M, Miazgowski T, KoÅ¼ybska M, Kotwas A, KorzeÅ„ M, Rudnicki B, Nogal T, Andrei CL, Ausloos M, Banach M, Brazinova A, Constantin MM, Dubljanin E, Herteliu C, Hostiuc M, Hostiuc S, Jakovljevic M, Jozwiak JJ, Kissimova-Skarbek K, KrÃ³l ZJ, Mestrovic T, Miazgowski B, Milevska Kostova N, Naghavi M, Negoi I, Negoi RI, Pana A, Rubino S, Sekerija M, Sierpinski R, Szponar L, Topor-Madry R, Vujcic IS, Widecka J, Widecka K, Wojtyniak B, Zadnik V, Kopec JA. | PLoS One |
| 18 | An immunogenic personal neoantigen vaccine for patients with melanoma | 1,010 | PubMed | 2017 | Ott PA, Hu Z, Keskin DB, Shukla SA, Sun J, Bozym DJ, Zhang W, Luoma A, Giobbie-Hurder | Nature |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | | | | | A, Peter L, Chen C, Olive O, Carter TA, et.al | |
| 19 | Patient-reported Outcomes of Patients With Breast Cancer During the COVID-19 Outbreak in the Epicenter of China: A Cross-sectional Survey Study | 1,005 | PubMed | 2020 | Juanjuan L, Santa-Maria CA, Hongfang F, Lingcheng W, Pengcheng Z, Yuanbing X, Yuyan T, Zhongchun L, Bo D, Meng L, Qingfeng Y, Feng Y, Yi T, Shengrong S, Xingrui L, Chuang C. | Clin Breast Cancer |
| 20 | Mortality prediction in intensive care units with the Super ICU Learner Algorithm (SICULA): a population-based study | 1,004 | PubMed | 2015 | Pirracchio R, Petersen ML, Carone M, Rigon MR, Chevret S, van der Laan MJ. | Lancet Respir Med |
| 21 | Machine Learning and Natural Language Processing in Mental Health: Systematic Review | 1,000 | PubMed | 2021 | Le Glaz A, Haralambous Y, Kim-Dufor DH, Lenca P, Billot R, Ryan TC, Marsh J, DeVylder J, Walter M, Berrouiguet S, Lemey C. | J Med Internet Res |
| 22 | Deep learning for liver tumor diagnosis part I: development of a convolutional neural network classifier for multi-phasic MRI | 974 | PubMed | 2019 | Hamm CA, Wang CJ, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Duncan JS, Weinreb JC, Chapiro J, Letzen B. | Eur Radiol |
| 23 | miRTarBase update 2018: a resource for experimentally validated microRNA-target interactions | 885 | PubMed | 2018 | Chou CH, Shrestha S, Yang CD, Chang NW, Lin YL, Liao KW, Huang WC, Sun TH, Tu SJ, Lee WH, Chiew MY, Tai CS, Wei TY, Tsai TR, Huang HT, Wang CY, | Nucleic Acids Res |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| 24 | Epidemiology and transmission of COVID-19 in 391 cases and 1286 of their close contacts in Shenzhen, China: a retrospective cohort study | 870 | PubMed | 2020 | Wu HY, Ho SY, Chen PR, Chuang CH, Hsieh PJ, Wu YS, Chen WL, Li MJ, Wu YC, Huang XY, Ng FL, Buddhakosai W, Huang PC, Lan KC, Huang CY, Weng SL, Cheng YN, Liang C, Hsu WL, Huang HD. Bi Q, Wu Y, Mei S, Ye C, Zou X, Zhang Z, Liu X, Wei L, Truelove SA, Zhang T, Gao W, Cheng C, Tang X, Wu X, Wu Y, Sun B, Huang S, Sun Y, Zhang J, Ma T, Lessler J, Feng T. | Lancet Infect Dis |
| 25 | Prediction of individual brain maturity using fMRI | 869 | PubMed | 2010 | Dosenbach NU, Nardos B, Cohen AL, Fair DA, Power JD, Church JA, Nelson SM, Wig GS, Vogel AC, Lessov-Schlaggar CN, Barnes KA, Dubis JW, Feczko E, Coalson RS, Pruett JR Jr, Barch DM, Petersen SE, Schlaggar BL. | Science |
| 26 | Comprehensive modeling of microRNA targets predicts functional non-conserved and non-canonical sites | 849 | PubMed | 2010 | Betel D, Koppal A, Agius P, Sander C, Leslie C. | Genome Biol |
| 27 | Graph-based prediction of Protein-protein interactions with attributed signed graph | 823 | PubMed | 2020 | Yang F, Fan K, Song D, Lin H. | BMC Bioinformatics |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | embedding | | | | | |
| 28 | Machine learning models predicting multidrug resistant urinary tract infections using "DsaaS" | 809 | PubMed | 2020 | Mancini A, Vito L, Marcelli E, Piangerelli M, De Leone R, Pucciarelli S, Merelli E. | BMC Bioinformatics |
| 29 | A Machine Learning Approach for Mortality Prediction in COVID-19 Pneumonia: Development and Evaluation of the Piacenza Score | 808 | PubMed | 2021 | Halasz G, Sperti M, Villani M, Michelucci U, Agostoni P, Biagi A, Rossi L, Botti A, Mari C, Maccarini M, Pura F, Roveda L, Nardecchia A, Mottola E, Nolli M, Salvioni E, Mapelli M, Deriu MA, Piga D, Piepoli M. | J Med Internet Res |
| 30 | An algorithm for direct causal learning of influences on patient outcomes | 807 | PubMed | 2017 | Rathnam C, Lee S, Jiang X. | Artif Intell Med |
| 31 | Predicting suicides after psychiatric hospitalization in US Army soldiers: the Army Study To Assess Risk and rEsilience in Servicemembers (Army STARRS) | 801 | PubMed | 2015 | Kessler RC, Warner CH, Ivany C, Petukhova MV, Rose S, Bromet EJ, et.al | JAMA Psychiatry |
| 32 | Natural Products for Drug Discovery in the 21st Century: Innovations for Novel Drug Discovery | 800 | PubMed | 2018 | Thomford NE, Senthebane DA, Rowe A, Munro D, Seele P, Maroyi A, Dzobo K. | Int J Mol Sci |
| 33 | Artificial Intelligence in Aptamer-Target Binding Prediction | 796 | PubMed | 2021 | Chen Z, Hu L, Zhang BT, Lu A, Wang Y, Yu Y, Zhang G. | Int J Mol Sci |
| 34 | Prediction of death status on the course of treatment in SARS-COV-2 patients with deep learning and machine learning methods | 793 | PubMed | 2021 | Kivrak M, Guldogan E, Colak C. | Comput Methods Programs Biomed |
| 35 | A comparative encyclopedia of DNA | 782 | PubMed | 2014 | Yue F, Cheng Y, Breschi A, | Nature |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | elements in the mouse genome | | | | Vierstra J, Wu W, Ryba T, Sandstrom R, Ma Z, Davis C, Pope BD, Shen Y, Pervouchine DD, Djebali S, Thurman RE, Kaul R, Rynes E, Kirilusha A, Marinov GK, Williams BA, Trout D, Amrhein, et al. | |
| 36 | DNA methylation-based classification of central nervous system tumours | 782 | PubMed | 2018 | Capper D, Jones DTW, Sill M, Hovestadt V, Schrimpf D, Sturm D, Koelsche C, Sahm F, Chavez L, Reuss DE, Kratz A, CM, MÃ¼ller HL, Rutkowski S, von Hoff K, FrÃ¼hwald MC, Gnekow A, Fleischhack G, Tippelt S, Calaminus G, Monoranu CM, Perry A, Jones C, et al. | Nature |
| 37 | Promoting synergistic research and education in genomics and bioinformatics | 777 | PubMed | 2008 | Yang JY, Yang MQ, Zhu MM, Arabnia HR, Deng Y. | BMC Genomics |
| 38 | Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification | 772 | PubMed | 2016 | Ellis K, Kerr J, Godbole S, Staudenmayer J, Lanckriet G. | Med Sci Sports Exerc |
| 39 | Architecture of the human regulatory network derived from ENCODE data | 770 | PubMed | 2018 | Gerstein MB, Kundaje A, Hariharan M, Landt SG, Yan KK, Cheng C, Mu XJ, Khurana E, Rozowsky J, Alexander R, Min R, Alves P, | Nature |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | | | | | Abyzov A, Addleman N, Bhardwaj N, Boyle AP, Cayting P, Charos A, Chen DZ, Cheng Y, Clarke D, Eastman C, et.al | |
| 40 | Deep neural networks for human microRNA precursor detection | 747 | PubMed | 2020 | Zheng X, Fu X, Wang K, Wang M. | BMC Bioinformatics |

## APPENDIX C

### Top 20 Highly Cited Documents in Dataset

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| 1 | Sparse MRI: The application of compressed sensing for rapid MR imaging | 4690 | SCOPUS | 2007 | Lustig M.; Donoho D.; Pauly J.M. | Magnetic Resonance in Medicine |
| 2 | Integrative analysis of 111 reference human epigenomes | 2,828 | PubMed | 2015 | Roadmap Epigenomics Consortium, Kundaje A, Meuleman W, Ernst J, Bilenky M, Yen A, Heravi-Moussavi A, Kheradpour P, Zhang Z, Wang J, Ziller MJ, Amin V, Whitaker JW, Schultz MD, Ward LD, Sarkar A, et.al | Nature |
| 3 | Temporal and Location Variations, and Link Categories for the Dissemination of COVID-19-Related Information on Twitter During the SARS-CoV-2 Outbreak in Europe: Infoveillance Study | 2,789 | PubMed | 2020 | Pobiruchin M, Zowalla R, Wiesner M. | J Med Internet Res |
| 4. | Correlation of Chest CT and RT-PCR Testing for Coronavirus Disease 2019 (COVID-19) in China: A Report of | 2,525 | PubMed | 2020 | Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, Tao Q, Sun Z, Xia L. | Radiology |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | 1014 Cases | | | | | |
| 5. | Dermatologist-level classification of skin cancer with deep neural networks | 1,998 | PubMed | 2017 | Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S. | Nature |
| 6 | Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation | 1907 | PubMed AND SCOPUS | 2017 | Kamnitsas K.; Ledig C.; Newcombe V.F.J.; Simpson J.P.; Kane A.D.; Menon D.K.; Rueckert D.; Glocker B. | Medical Image Analysis |
| 7 | The interaction of domain knowledge and linguistic structure in natural language processing: interpreting hypernymic propositions in biomedical text | 1,787 | PubMed | 2003 | Rindflesch TC, Fiszman M. | J Biomed Inform |
| 8 | The evaluation of tumor-infiltrating lymphocytes (TILS) in breast cancer: Recommendations by an International TILS Working Group 2014 | 1560 | SCOPUS | 2015 | Salgado R.; Denkert C.; Demaria S.; Sirtaine N.; Klauschen F.; Pruneri G.; Wienert S.; Van den Eynden G.; Baehner F.L.; Penault-Llorca F.; Perez E.A.; Thompson E.A.; Symmans W.F. | Annals of Oncology |
| 9 | Optimizing taxonomic classification of marker-gene amplicon sequences with QIIME 2's q2-feature-classifier plugin | 1540 | SCOPUS | 2018 | Bokulich N.A.; Kaehler B.D.; Rideout J.R.; Dillon M.; Bolyen E.; Knight R.; Huttley G.A.; Gregory Caporaso J. | Microbiome |
| 10 | Deep convolutional neural network for segmentation of knee joint anatomy | 1,477 | PubMed | 2018 | Zhou Z, Zhao G, Kijowski R, Liu F. | Magn Reson Med |
| 11 | Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging | 1,477 | PubMed | 2019 | Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, | Eur Radiol |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | features | | | | Duncan JS, Chapiro J, Letzen B. | |
| 12 | Genetic effects on gene expression across human tissues | 1,468 | PubMed | 2017 | GTEx Consortium; Laboratory, Data Analysis &Coordinating Center (LDACC),et.al | Nature |
| 13 | Early prediction of level-of-care requirements in patients with COVID-19 | 1,324 | PubMed | 2020 | Hao B, Sotudian S, Wang T, Xu T, Hu Y, Gaitanidis A, Breen K, Velmahos GC, Paschalidis IC. | Elife |
| 14 | Learning to control a brain-machine interface for reaching and grasping by primates | 1307 | SCOPUS | 2003 | Carmena J.M.; Lebedev M.A.; Crist R.E.; O'Doherty J.E.; Santucci D.M.; Dimitrov D.F.; Patil P.G.; Henriquez C.S.; Nicolelis M.A.L. | PLoS Biology |
| 16 | Predicting small-molecule pharmacokinetic and toxicity properties using graph-based signatures | 1282 | SCOPUS | 2015 | Pires D.E.V.; Blundell T.L.; Ascher D.B. | Journal of Medicinal Chemistry |
| 17 | Automated detection of COVID-19 cases using deep neural networks with X-ray images | 1243 | PubMed AND SCOPUS | 2020 | Ozturk T.; Talo M.; Yildirim E.A.; Baloglu U.B.; Yildirim O.; Rajendra Acharya U. | Computers in Biology and Medicine |
| 18 | Logistic regression and artificial neural network classification models: A methodology review | 1197 | PubMed AND SCOPUS | 2002 | Dreiseitl S.; Ohno-Machado L. | Journal of Biomedical Informatics |
| 19 | Integrated problem-based learning versus lectures: a path analysis modelling of the relationships between educational context and learning approaches | 1,193 | PubMed | 2018 | Gustin MP, Abbiati M, Bonvin R, Gerbase MW, Baroffio A. | Med Educ Online |
| 20 | Large-scale mapping and validation of Escherichia coli transcriptional | 1102 | SCOPUS | 2007 | Faith J.J.; Hayete B.; Thaden J.T.; Mogno I.; Wierzbowski J.; | PLoS Biology |

| Counter | Title | Total Citations | Research Source | Year | Authors | Journal/ Book |
|---|---|---|---|---|---|---|
| | regulation from a compendium of expression profiles | | | | Cottarel G.; Kasif S.; Collins J.J.; Gardner T.S. | |

## Appendix D

### Top 20 Keywords and Their Weights

| Count | Weight | Keyword |
|---|---|---|
| 1. | 17872 | humans |
| 2. | 12847 | machine learning |
| 3. | 6962 | deep learning |
| 4. | 5938 | artificial intelligence |
| 5. | 5212 | female |
| 6. | 4891 | algorithms |
| 7. | 4733 | male |
| 8. | 3000 | middle aged |
| 9. | 2860 | adult |
| 10. | 2723 | neural networks computer |
| 11. | 2504 | aged |
| 12. | 1623 | magnetic resonance imaging |
| 13. | 1552 | retrospective studies |
| 14. | 1367 | covid-19 |
| 15. | 1299 | brain |
| 16. | 1259 | young adult |
| 17. | 1258 | reproducibility of results |
| 18. | 1233 | prognosis |
| 19. | 1172 | animals |
| 20. | 1055 | support vector machine |