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Revival of Classical Algorithms: A Bibliometric Study on the Trends of Neural Networks and Genetic Algorithms

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Abstract: The purpose of our bibliometric research was to capture and analyze the trends of two types of well-known classical artificial intelligence (AI) algorithms: neural networks (NNs) and genetic algorithms (GAs). *Symmetry* is a very popular international and interdisciplinary scientific journal that cover six major research subjects of mathematics, computer science, engineering science, physics, biology, and chemistry which are all related to our research on classical AI algorithms; therefore, we referred to the most innovative research articles of classical AI algorithms that have been published in *Symmetry*, which have also introduced new advanced applications for NNs and Gas. Furthermore, we used the keywords of "neural network algorithm" or "artificial neural network" to search the SSCI database from 2002 to 2021 and obtained 951 NN publications. For comparison purposes, we also analyzed GA trends by using the keywords "genetic algorithm" to search the SSCI database over the same period and we obtained 878 GA publications. All of the NN and GA publication results were categorized into eight groups for deep analyses so as to investigate their current trends and forecasts. Furthermore, we applied the Kolmogorov–Smirnov test (K–S test) to check whether our bibliometric research complied with Lotka's law. In summary, we found that the number of applications for both NNs and GAs are continuing to grow but the use of NNs is increasing more sharply than the use of GAs due to the boom in deep learning development. We hope that our research can serve as a roadmap for other NN and GA researchers to help them to save time and stay at the cutting edge of AI research trends.

Keywords: algorithm; neural network; artificial neural network; genetic algorithm; bibliometric; artificial intelligence; AI; Lotka's law

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1. Introduction

1.1. Neural Networks

The history of neural networks dates back to the 1940s. The research article of McCulloch and Pitts published in 1943 is often regarded as the beginning of the neural network concept [1]. During the 1950s and 1960s, the first neuro-computer was developed by Frank Rosenblatt and others [2]. Since then, neural networks have continued to gain attention, especially with the rise of deep learning.

Neural networks are one of the many forms of classical artificial intelligence algorithms, also known as artificial neural networks (ANNs). The inspiration for NNs arose from the sophisticated functionality of human brains, with the aim of simulating the way neurons and other nerve cells transmit electrical impulses to each other. NN are composed of three types of layers: an input layer, more than one intermediate layers (hidden layers), and an output layer [3]. Each NN node is connected to another, and they have associated weights and thresholds. When the output of a node is higher than a certain threshold, the specified node is activated and the information is transmitted to the next layer of the NN; otherwise, no information is transmitted to the next layer.

It should be noted that neural network algorithms rely on huge amounts of data to train their learning models and subsequently improve their accuracy. Nevertheless, when these learning models are fine-tuned to achieve high accuracy, they become powerful artificial intelligence tools that can classify and cluster data at extremely high speeds. Taking image recognition as an example, neural network algorithms only take a few minutes to process image recognition data, while human experts need hours for manual image recognition [4].

1.2. Genetic Algorithms

GAs are another form of classical artificial intelligence algorithms which are usually used to solve process optimization problems, such as travel time optimization for the transportation industry and the optimization of computer architectures, computer networks, and investment portfolios. Hybrid solutions involving both NNs and GAs have also been developed, for instance, for parameter selection in machine learning model training [5]. GAs were based on the concept of Charles Darwin's biological evolution theory of natural selection and apply the methodologies of evolution, including inheritance, natural selection, mutation, and crossover. On the basis of Darwin's most famous rule of the "survival of the fittest", GAs simulate the evolutionary mechanisms of natural selection to produce the fittest options and reproduce the best descendants through mutations and crossovers [6]. In other words, the better genes from the fittest organisms are naturally selected and evolve to produce more superior descendants, i.e., organisms evolve to become progressively fitter for their specific environments [7,8].

GAs became more well-known with the assistance of John Holland's research in 1975. Since then, GAs have been applied in a great deal of research domains, including assembly line balancing, factory layout problems, project scheduling, travel scheduling, and in particular, global optimization problems [9,10].

GAs are heuristic algorithms that simulate the evolutionary mechanism of natural selection to produce the fittest options, replace unfit solutions, and reproduce the best descendants through mutation and crossovers. The process of natural selection is repeated until the best result has been produced [8].

1.3. Genetic Algorithms and Neural Networks

Genetic algorithms and neural networks are both forms of classical algorithms, but GAs have been more popular in the past because they do not require a large amount of data for processing. AI has achieved exceptional accomplishments in recent years, mainly because of the rise of NN-based machine learning. NNs have now become more popular and have become ingrained in our everyday lives. Nevertheless, GAs are still widely used today and the number of applications for GAs has been steadily growing in science, engineering, social sciences, and numerous other fields. An increasing number of AI applications combine GAs and NNs to unlock new solutions. The new combined solutions breathe new life into the field of AI solutions and can speed up the entire process of solving specific problems [11,12].

2. Literature Review

2.1. Applications for Neural Networks

Neural networks are used for a wide range of applications, including applications in computing, science, engineering, technology, environmental, agriculture, mining, climate, business, arts, and more. Some modern applications for neural networks have also been developed, including image recognition, speech recognition, character recognition, machine translation, stock market predictions, medical diagnosis [1], counterfeit products classification [13], sound-absorbing board optimization [14], the optimization of channel equalization in wireless communication [15], the optimization of IoT intrusion detection system performance [16], diabetic retinopathy classification [17], the mitigation of cybersecurity alert fatigue [18], the optimization of hand gesture recognition [19], optimization of indoor human activity recognition [20], the optimization of multi-type object tracking [21], the mitigation of global warming impacts on marine ecosystems [22], the optimization of oil layer prediction [23], the identification of the optimal parameters for recurrent neural network training [24] and the optimal classification of noises in QR codes [25]. Among all these NN applications, the most successful and famous application for neural networks is image recognition, which is based on the convolutional neural network (CNN) architecture. We discuss this in more detail later in the paper.

There are diverse applications for neural networks, but some of them have become more popular in every everyday life, a few examples of which are listed below.

1. Facial Recognition

Facial recognition systems are becoming more popular as intelligent surveillance systems. Facial recognition solutions map out human faces and compare them to previously stored images. These systems are often used for specific entrances in buildings to authenticate human faces and match them up with the data that are stored in their facial image databases.

As stated above, CNNs are often used for image recognition processing. For this, a large number of images of human faces are imported into a database to train the CNNs, although the stored human face images need further processing before the CNN training. CNN models are based on linear algebra principles and matrix multiplication is key for the representation of data and weights. The basic structure of CNNs comprise three layers: a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer consists of many filters and features and applies those filters to the input to generate feature maps using an activation function. The second layer is the pooling layer, the function of which is to downsample the feature maps. Finally, the fully connected layer, which is also known as the classifier, consists of an activation function to classify the images [26].

Below are some examples of advanced applications for neural networks within facial recognition:

- The aggregation of the spatial and temporal convolutional features of CNN for video-based facial expression recognition [27].
- The use of hybrid data augmentation and lightweight convolutional neural network solutions to estimate the age of faces in images [28].
- Improved accuracy in facial emotion recognition using new hybrid HOG-ESRs (histogram of oriented gradient-ensembles with shared representations) algorithm [29].

2. Speech recognition

Speech recognition is another example of technology that has now become so common in our daily lives that is used without a second thought. Through popular voice-controlled systems, such as Amazon's Alexa and Apple's Siri, automatic speech recognition (ASR) is scattered throughout our computers, tablet devices, home speakers, and cellar phones. ASR technology is now also being used in businesses, for instance, in customer service and many other areas. Enterprises have immediately embraced ASR technology as a means to develop operational efficiencies and simplify processes.

Neural networks have been applied in speech recognition technology for some time. Recurrent neural network (RNNs) are a unique type of NN that have the concept of "memory" which were originally designed for sequential data processing. RNNs have been employed to develop speech recognition systems with dramatic success. Moreover, a special and powerful RNN architecture with improved memory has been developed which is known as long short-term memory (LSTM). LSTM has proven to be especially effective in speech recognition [30,31].

Below are some examples of advanced applications for neural networks within speech recognition:

- A convolutional neural network (CNN) structure that can divide continuous speech into syllables by converting sound patterns into the form of RGB (red, green, blue) images [32];
- A hybrid CNN and bi-directional long short-term memory (BiLSTM) model for a cross-language end-to-end speech recognition system based on transfer learning [33];

- A hybrid residual time delay neural network (ResTDNN) and BiLSTM model for slot filling in speech recognition [34].

2.2. Applications for Genetic Algorithms

Numerous researchers and scientists have applied genetic algorithms in mathematics, computer science, engineering, business, finance, economics, and social sciences. Many scientists have applied GA concepts to computer science problems, such as the optimization of computer architectures [35,36]. Another important topic of study is the optimization of distributed computer networks. The main objective of this research is to minimize the costs of designing distributed computer network topologies [37]. Other applications have also been developed, such as file allocation methods for distributed systems, signal processing and filtering, hardware debugging, and more. In the finance sector, GAs are used for the automation of sophisticated trading systems, the valuation of real options, and portfolio optimization [38,39]. GAs are also used to solve problems in industry, management, and engineering, for instance, airline revenue management, container loading optimization, automated planning of structural inspection, control engineering, mechanical engineering, marketing mix analysis, optimization of mobile communications infrastructure, plant floor layout design, quality control management, bearing placement optimization, and the identification of optimal routes for multiple vehicles [40–44]. Clearly, GAs can be applied to solve a broad range of general solutions [45–47].

Below are some examples of advanced applications for genetic algorithms:

- A novel aggregated multi-objective genetic algorithm (MOGA) and a variant particle swarm optimization (PSO) solution for 5G software-defined networking (SDN) architecture [48];
- Combined support vector machine (SVM) and GA solutions for the detection of cyber-attacks and malicious intrusions [49];
- An integrated auto-generated multi-attribute design structure matrix (DSM) and GA solution for modular design [50];
- A GA mechanism that can optimize proof-of-work (PoW) blockchains parameters [51].

2.3. Applications for Combination of Genetic Algorithms and Neural Networks

The first attempt at combining genetic algorithms and neural networks was in the late 1980s. Since then, many researchers and scholars have published articles about applications for genetic algorithms and neural networks (GANNs). Various combined genetic algorithm and neural network approaches have been explored, including solar system performance prediction [11], face recognition [52], animation [53], color recipe prediction [54], crude fractional distillation processing [55], and more. In fact, several combinations of genetic algorithms and neural networks have been developed by researchers. Schaffer et al. found that these GANN combinations can be categorized into two different groups: supportive combinations and collaborative combinations. NNs and GAs are applied sequentially in supportive combinations and simultaneously in collaborative combinations [12,56,57]. GAs can also be used in machine learning for feature selection in recurrent neural networks and for training artificial neural networks when pre-classified examples are not available [58].

Below are some examples of advanced applications for NN and GA combinations:

- A hybrid cascade neural network and metaheuristic optimization genetic algorithm for space–time forecasting [59];
- A combined GA and back-propagation (BP) neural network for early warning systems in coal mines. [60];
- An integrated NN and GA framework for sequential semi-supervised classification [61].

2.4. Laws of Bibliometrics

Statistical and mathematical methods are usually applied to analyze information about publications which involve three important laws of bibliometrics: Lotka's law, Bradford's law, and Zipf's law. These three classical laws are the pillars of bibliometrics and are often applied in bibliometric research to test the applicability of publications [62–64].

2.4.1. Lotka's Law

Lotka's law determines the productivity of authors within specified research areas. The law states that 60% of authors in a specified research area only publish one article, 15% publish two articles ($1/2^2 \times 0.60$), 7% publish three articles ($1/3^2 \times 0.60$), etc. When Lotka's law is applied to several articles over a specified time period, the results are similar but not very accurate. Lotka's law is used to assess the frequency with which authors publish articles online [65–67]. Lotka's law is also deemed to be quite useful for studying the productivity patterns of authors in bibliographies. In this research, we selected articles published between 2002 and 2021 and performed an author productivity check to observe the NN and GA research trends and forecasts. For verification purposes, we also applied the K–S test to check whether our results complied with Lotka's inverse square law [68–70].

2.4.2. Zipf's Law

Zipf's law is regularly described as the word frequency law and is used to identify the frequency distribution of words within articles. It states that the most frequent word in a long article is used twice as often as the second most frequent word and three times as often as the third most frequent word, etc. Zipf's law is not statistically accurate but it is still quite valuable for bibliometric researchers [71,72].

2.4.3. Bradford's Law

Bradford's law is a universal bibliometric principle that determines the number of core journals within specified research area. Bradford's law separates the core journals within a research area into three categories with an equal number of articles. The first category comprises the core journals on the subject, which tend to be fewer in number but produce approximately one-third of the articles. The second category comprises the same number of articles, but a larger number of journals. The third category comprises the same number of articles but a much larger number of journals. Bradford found that the relationships between the journals in the first category and those in the second and third category were proportional ($1: n: n^2$). Bradford studied 326 geophysics journals and their bibliographies and found that 429 articles were included in 9 journals, 499 articles were included in 59 journals, and 404 articles were included in 258 journals; the proportion was 9: 59: 258, which was similar to 9: 45: 225. Based on this, it can be seen that Bradford's law is not very precise but it is still deemed to be a general bibliometric principle by many researchers [71,73].

3. Materials and Methods

3.1. Research Methods

In this research, we studied articles published from 2002 to 2021. All of the data that we collected were from the Social Science Citation Index (SSCI) on the Web of Science platform. SSCI indexes over 3400 internationally famous social sciences journals across over 50 social sciences research areas and allows scholars to search articles using different criteria, such as subject, citation, country, territory, document type, institution name, research area, source title, journal, author, etc. [73].

Bibliometric methods are types of study systems that are often used in library science and informatics research and use statistical analyses to identify publication patterns in specific research areas. For instance, scholars can use bibliometric methods to assess the impacts of the relationships between one or more writers or articles. Analytical bibliometric methods mostly involve accessing SSCI and/or the Science Citation Index (SCI) databases to collect data, trace citations, and assess impact. Analytical bibliometric methods can help to identify innovative fields of study and possible research directions [72,73].

3.2. Research Analysis and Discussion

3.2.1. Analysis by Publication Year

We first found an obvious ascending trend in the number of NN articles published since 2015 and a smoother ascending trend in the number of GA articles published since 2016 (Figure 1). The rapid upward trend of NN articles could be explained by the third wave of artificial intelligence development. In 2015, Microsoft used a deep learning technique (i.e., a deep neural network) to outperform humans in image recognition, which sparked the third wave of AI advancement (He et al., 2016) [74]. Based on this, we could also conclude that the smoother ascending trend of GA articles published since 2016 was due to the revolutionary deep learning technique also breathing new life into GA research. Second, we concluded from the results that NN research and development have been rapidly and continuously growing for quite some time. Furthermore, although GAs have been around for a long time, they are still keeping up with the times and developing steadily.

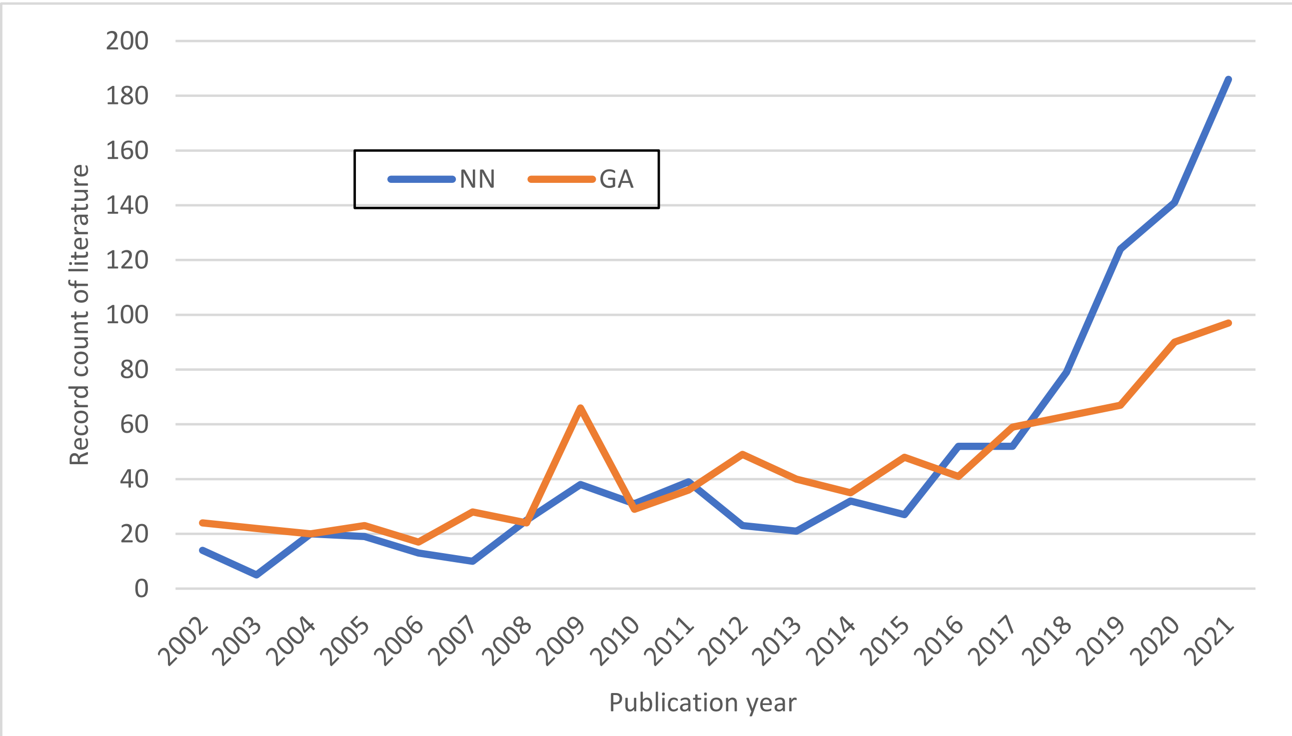

Figure 1. The trend of NN and GA literature publication (source: SSCI database).

3.2.2. Analysis by Citation

The trends of NN and GA citations both increased rapidly from 2018, which could also be explained by the third wave of AI development (Figure 2). We concluded that the ascending trends of NN and GA citations will continue for some time as long as the AI industry is booming.

3.2.3. Analysis by Country/Territory

From Table 1 and Figure 3, it can be seen that China produced the highest quantity of NN and GA research publications, followed by the USA. Some people believe that whichever country first masters AI technology will rule the world and from our results, the significance of AI within the context of U.S.–China confrontation can clearly be seen. Iran and Taiwan were in third place for the number of NN and GA publications, although the results showed that they are now starting to catch up with other countries. Furthermore, we also found that the NN and GA publications from top three countries made up over 50% of the total number of articles and that AI research was concentrated in a few countries. We discovered that Turkey, South Korea, and Spain are also catching up quickly and becoming major contributors to NN and GA research. Figure 3 shows the top six countries for NN and GA publications.

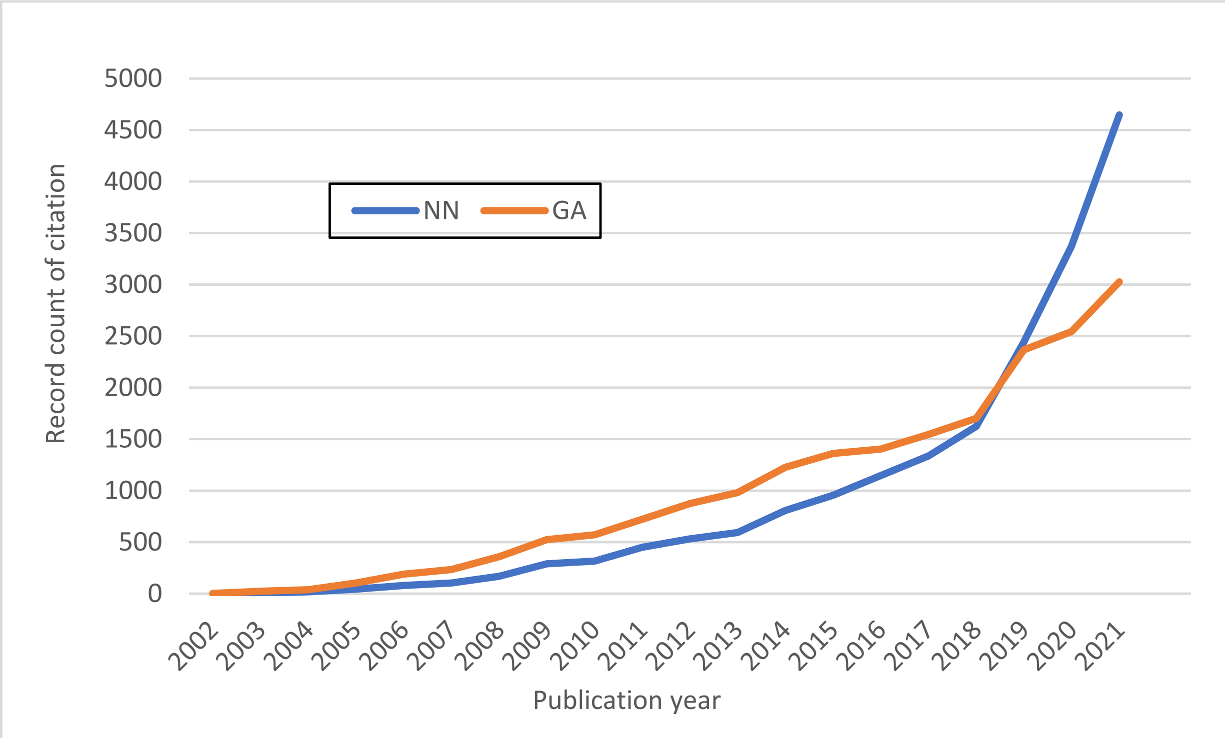

Figure 2. Trends of NN and GA citations per year (source: SSCI database).

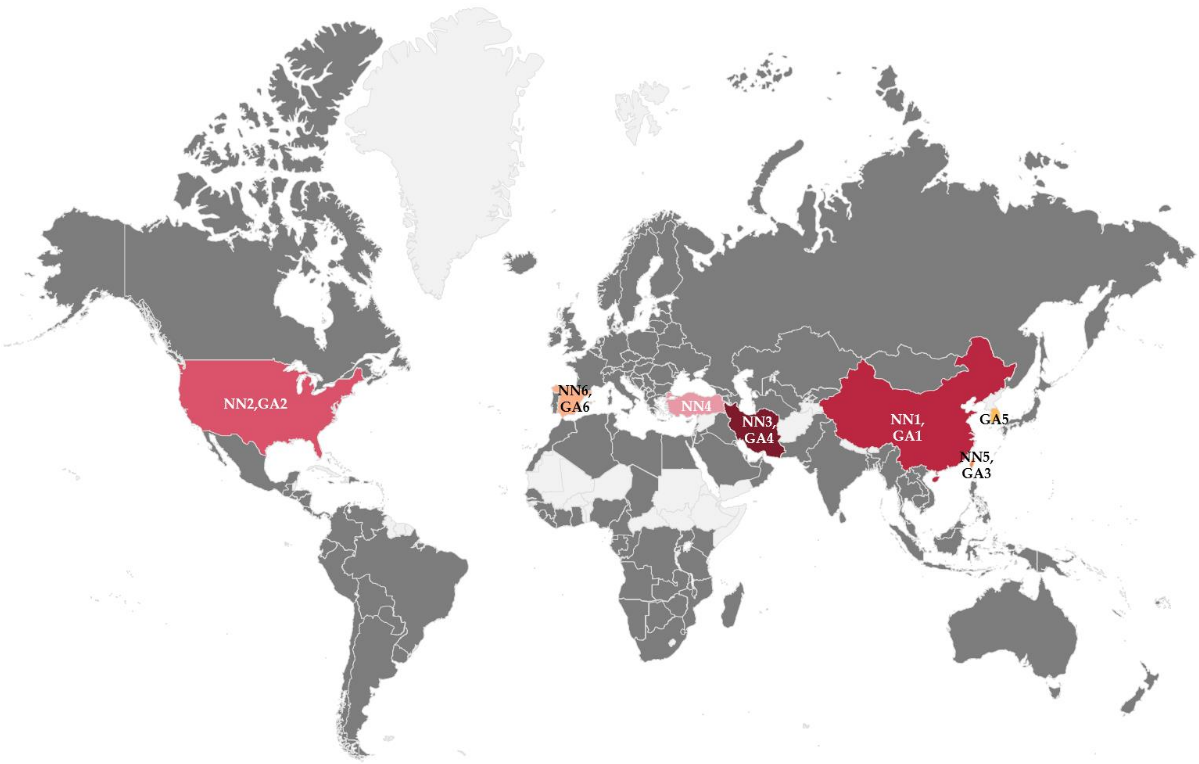

Figure 3. The top six countries/territories for NN and GA publications (source: SSCI database).

Table 1. A list of top 25 countries/territories producing NN and GA articles (from 2002 to 2021, SSCI).

Ranking	Neural Network			Genetic Algorithm		
	Countries/Territories	**NP**	**% of 951**	**Countries/Territories**	**NP**	**% of 878**
1	PEOPLES R CHINA	177	18.612	PEOPLES R CHINA	209	23.804
2	USA	169	17.771	USA	163	18.565
3	IRAN	89	9.359	TAIWAN	81	9.226
4	TURKEY	66	6.94	IRAN	72	8.2
5	TAIWAN	56	5.889	SOUTH KOREA	54	6.15
6	SPAIN	47	4.942	SPAIN	52	5.923
7	ITALY	46	4.837	ENGLAND	47	5.353
8	CANADA	45	4.732	INDIA	45	5.125
9	ENGLAND	43	4.522	TURKEY	34	3.872
10	MALAYSIA	42	4.416	CANADA	32	3.645
11	SOUTH KOREA	39	4.101	AUSTRALIA	29	3.303
12	INDIA	35	3.68	ITALY	25	2.847
13	GERMANY	31	3.26	FRANCE	21	2.392
14	POLAND	25	2.629	GERMANY	19	2.164
15	AUSTRALIA	24	2.524	JAPAN	19	2.164
16	FRANCE	24	2.524	BRAZIL	18	2.05
17	BRAZIL	21	2.208	PORTUGAL	17	1.936
18	NETHERLANDS	21	2.208	GREECE	14	1.595
19	JAPAN	18	1.893	NETHERLANDS	14	1.595
20	PAKISTAN	17	1.788	COLOMBIA	13	1.481
21	SAUDI ARABIA	17	1.788	MEXICO	12	1.367
22	PORTUGAL	15	1.577	MALAYSIA	11	1.253
23	SOUTH AFRICA	14	1.472	SINGAPORE	11	1.253
24	GREECE	13	1.367	BELGIUM	9	1.025
25	EGYPT	11	1.157	CHILE	8	0.911

NP = number of publications.

3.2.4. Analysis by Institution Name

In Table 2, it can be seen that the University of Tehran was the top institution for NN research and the Islamic Azad University was the top institution for GA research. Both are institutions in Iran and both published over 20 articles (2.103% and 2.506%). The Universiti Malaya was the second-place institution for NN research with 17 articles (1.788%) and Hong Kong Polytech University was the second-place institution for GA research with 13 articles (1.481%). The third-place institution for NN research was the Islamic Azad University and the third-place institution for GA research was the Iran University of Science and Technology. Furthermore, we also found that Iran was the most productive country for NN and GA research.

3.2.5. Analysis by Document Type

From Table 3, it can be seen that 92.429% of NN research was in the form of articles (879 articles) and 96.128% of GA research was in the form of articles (844 articles). We concluded that articles were the major and most accepted document type for NN and GA research publications.

Table 2. A list of the top 25 institutions producing NN and GA publications (from 2002 to 2021, SSCI).

Ranking	Neural Network				Genetic Algorithm			
	Institution Names	**NP**	**% of 951**	**Country**	**Institution Names**	**NP**	**% of 878**	**Country**
1	UNIV OF TEHRAN	20	2.103	Iran	ISLAMIC AZAD UNIV	22	2.506	Iran
2	UNIVERSITI MALAYA	17	1.788	Malaysia	HONG KONG POLYTECHNIC UNIV	13	1.481	China
3	ISLAMIC AZAD UNIV	16	1.682	Iran	IRAN UNIV SCIENCE TECHNOLOGY	12	1.367	Iran
4	STATE UNIV SYSTEM OF FLORIDA	15	1.577	USA	NATIONAL INSTITUTE OF TECHNOLOGY	12	1.367	India
5	EGYPTIAN KNOWLEDGE BANK EKB	11	1.157	Egypt	PENNSYLVANIA COMMONWEALTH SYSTEM OF HIGHER EDUCATION	11	1.253	USA
6	IRAN UNIV SCIENCE TECHNOLOGY	11	1.157	Iran	SHARIF UNIV OF TECHNOLOGY	11	1.253	Iran
7	PENNSYLVANIA COMMONWEALTH SYSTEM OF HIGHER EDUCATION	10	1.052	USA	UNIVERSITAT POLITECNICA DE VALENCIA	11	1.253	Spain
8	CHINESE ACADEMY OF SCIENCES	9	0.946	China	UNIV OF TEHRAN	11	1.253	Iran
9	INDIAN INSTITUTE OF TECHNOLOGY SYSTEM	9	0.946	India	BEIJING JIAOTONG UNIV	10	1.139	China
10	UCSI UNIV	9	0.946	Malaysia	INDIAN INSTITUTE OF TECHNOLOGY SYSTEM	10	1.139	India
11	UNIVERSITI TEKNOLOGI MALAYSIA	9	0.946	Malaysia	PENNSYLVANIA STATE UNIV	10	1.139	USA
12	UNIV OF ALBERTA	9	0.946	Canada	NATIONAL CHENG KUNG UNIV	9	1.025	Taiwan
13	UNIV OF LONDON	9	0.946	UK	STATE UNIV SYSTEM OF FLORIDA	9	1.025	USA
14	UNIV OF TUNKU ABDUL RAHMAN	9	0.946	Malaysia	YONSEI UNIV	9	1.025	Korea
15	CENTRAL SOUTH UNIV	8	0.841	China	CHINESE ACADEMY OF SCIENCES	8	0.911	China
16	DELFT UNIV OF TECHNOLOGY	8	0.841	Netherlands	NATIONAL UNIV OF SINGAPORE	8	0.911	Singapore
17	HONG KONG POLYTECHNIC UNIV	8	0.841	China	TSINGHUA UNIV	8	0.911	China
18	PENNSYLVANIA STATE UNIV	8	0.841	USA	UNIV OF MICHIGAN	8	0.911	USA
19	SHARIF UNIV OF TECHNOLOGY	8	0.841	Iran	UNIV OF MICHIGAN SYSTEM	8	0.911	USA
20	UDICE FRENCH RESEARCH UNIVERSITIES	8	0.841	France	WUHAN UNIV	8	0.911	China
21	CENTRE NATIONAL DE LA RECHERCHE SCIENTIFIQUE CNRS	7	0.736	France	AMIRKABIR UNIV OF TECHNOLOGY	7	0.797	Iran
22	ISFAHAN UNIV OF TECHNOLOGY	7	0.736	Iran	NATIONAL KAOHSIUNG UNIV OF SCIENCE TECHNOLOGY	7	0.797	Taiwan
23	ISTANBUL TECHNICAL UNIV	7	0.736	Turkey	SEOUL NATIONAL UNIV SNU	7	0.797	Korea
24	SANTA CLARA UNIV	7	0.736	USA	TARBIAT MODARES UNIV	7	0.797	Iran
25	TARBIAT MODARES UNIV	7	0.736	Iran	UNIVERSIDADE DO PORTO	7	0.797	Portugal

NP = number of publications.

Table 3. The different document types in NN and GA research (from 2002 to 2021, SSCI).

Neural Network			Genetic Algorithm		
Document Type	**NP**	**% of 951**	**Document Type**	**NP**	**% of 878**
Article	879	92.429	Article	844	96.128
Meeting Abstract	38	3.996	Proceeding Paper	36	4.1
Review Article	24	2.524	Meeting Abstract	13	1.481
Proceeding Paper	13	1.367	Book Review	11	1.253
Early Access	11	1.157	Review Article	8	0.911
Correction	4	0.421	Early Access	7	0.797
Editorial Material	3	0.315	Correction	2	0.228
Book Review	2	0.21			
Letter	1	0.105			
Retracted Publication	1	0.105			

NP = number of publications.

3.2.6. Analysis by Language

From Table 4, it can be seen that English was the major language for NN and GA research papers, with 941 and 872 articles (98.948% and 99.317%), respectively. As English is the predominant scientific language worldwide and is the most widely used language among scientists, we could conclude that English was the number one language used in NN and GA research publications.

Table 4. The languages used for NN and GA research (from 2002 to 2021, SSCI).

Neural Network			Genetic Algorithm		
Language	**NP**	**% of 951**	**Language**	**NP**	**% of 878**
English	941	98.948	English	872	99.317
Portuguese	3	0.315	Spanish	3	0.342
Spanish	2	0.21	Czech	2	0.228
Czech	1	0.105	Turkish	1	0.114
French	1	0.105			
German	1	0.105			
Russian	1	0.105			
Turkish	1	0.105			

NP = number of publications.

3.2.7. Analysis by Research Area

From Table 5**,** the top three NN research areas can be identified: computer science, with 221 articles (23.239%); engineering, with 201 articles (21.136%); and environmental sciences ecology, with 186 articles (19.558%). Table 5 also shows the top three GA research areas: computer science, with 301 articles (34.282%); engineering, with 280 articles (31.891%); and operation research, with 228 articles (25.968%). From this, it can be seen that computer science and engineering were the major topics within NN and GA research and that environmental sciences ecology research is catching up due to the rapid development of ESG. Furthermore, many other important and potential research domains for NN and GA publications were identified, such as business economies, mathematics, psychology, transportation, information science, library science, energy, etc.

Table 5. An analysis of NN and GA research areas (from 2002 to 2021, SSCI).

Ranking	Neural Network			Genetic Algorithm		
	Research Areas	**NP**	**% of 951**	**Research Areas**	**NP**	**% of 878**
1	Computer Science	221	23.239	Computer Science	301	34.282
2	Engineering	201	21.136	Engineering	280	31.891
3	Environmental Sciences Ecology	186	19.558	Operations Research Management Science	228	25.968
4	Business Economics	158	16.614	Business Economics	221	25.171
5	Science Technology Other Topics	124	13.039	Environmental Sciences Ecology	111	12.642
6	Operations Research Management Science	84	8.833	Mathematics	91	10.364
7	Psychology	84	8.833	Science Technology Other Topics	67	7.631
8	Public Environmental Occupational Health	67	7.045	Transportation	62	7.062
9	Energy Fuels	55	5.783	Information Science Library Science	37	4.214
10	Mathematics	50	5.258	Geography	36	4.1
11	Transportation	47	4.942	Psychology	23	2.62
12	Neurosciences Neurology	43	4.522	Physical Geography	21	2.392
13	Social Sciences Other Topics	33	3.47	Public Administration	19	2.164
14	Physics	27	2.839	Energy Fuels	18	2.05
15	Health Care Sciences Services	25	2.629	Public Environmental Occupational Health	17	1.936
16	Information Science Library Science	20	2.103	Social Sciences Other Topics	17	1.936
17	Materials Science	19	1.998	Automation Control Systems	15	1.708
18	Chemistry	18	1.893	Mathematical Methods In Social Sciences	15	1.708
19	Geography	18	1.893	Telecommunications	13	1.481
20	Telecommunications	18	1.893	Education Educational Research	11	1.253
21	Education Educational Research	16	1.682	Physics	11	1.253
22	Psychiatry	14	1.472	Urban Studies	10	1.139
23	Mathematical Methods in Social Sciences	13	1.367	Chemistry	8	0.911
24	Physical Geography	13	1.367	Geology	7	0.797
25	Geology	12	1.262	Health Care Sciences Services	7	0.797

NP = number of publications.

3.2.8. Analysis by Source Title

From Table 6, the top three NN research source titles can be identified: *Sustainability*, with 75 articles (7.886%); *Expert Systems with Applications*, with 41 articles (4.311%); and the *International Journal of Environmental Research and Public Health*, with 25 articles (2.629%). Table 6 also shows the top three GA research source titles: *Expert Systems with Applications*, with 63 articles (7.175%); *Sustainability*, with 44 articles (5.011%); and the *Journal of Operational Research Society*, with 25 articles (2.847%). We could use these data to foresee the major NN and GA research trends. Furthermore, many other important research source titles for NN and GA publications were identified, such as *Neural Computing Applications*, *Energy Policy*, *PLoS ONE*, *Applied Soft Computing*, *Computational Economics*, *Computers Industrial Engineering*, etc.

Table 6. An analysis of the source titles in NN and GA research (from 2002 to 2021, SSCI).

Ranking	Neural Network			Genetic Algorithm		
	Source Title	NP	% of 951	Source Title	NP	% of 878
1	SUSTAINABILITY	75	7.886	EXPERT SYSTEMS WITH APPLICATIONS	63	7.175
2	EXPERT SYSTEMS WITH APPLICATIONS	41	4.311	SUSTAINABILITY	44	5.011
3	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	25	2.629	JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY	25	2.847
4	NEURAL COMPUTING APPLICATIONS	19	1.998	APPLIED SOFT COMPUTING	24	2.733
5	ENERGY POLICY	16	1.682	COMPUTATIONAL ECONOMICS	17	1.936
6	PLoS ONE	16	1.682	COMPUTERS INDUSTRIAL ENGINEERING	16	1.822
7	APPLIED SCIENCES BASEL	13	1.367	INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE	15	1.708
8	NEUROCOMPUTING	11	1.157	OMEGA INTERNATIONAL JOURNAL OF MANAGEMENT SCIENCE	15	1.708
9	COMPUTATIONAL ECONOMICS	10	1.052	INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH	13	1.481
10	ENERGIES	10	1.052	COMPUTERS ENVIRONMENT AND URBAN SYSTEMS	11	1.253
11	ENERGY	10	1.052	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	11	1.253
12	IEEE ACCESS	9	0.946	COMPUTERS OPERATIONS RESEARCH	10	1.139
13	ACCIDENT ANALYSIS AND PREVENTION	8	0.841	EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	10	1.139
14	APPLIED SOFT COMPUTING	8	0.841	INFORMATION PROCESSING MANAGEMENT	10	1.139
15	JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY	8	0.841	SOFT COMPUTING	9	1.025
16	FRONTIERS IN PSYCHOLOGY	7	0.736	ECONOMIC COMPUTATION AND ECONOMIC CYBERNETICS STUDIES AND RESEARCH	8	0.911
17	IRANIAN JOURNAL OF PUBLIC HEALTH	7	0.736	TRANSPORTATION RESEARCH PART E LOGISTICS AND TRANSPORTATION REVIEW	8	0.911
18	JOURNAL OF INTELLIGENT FUZZY SYSTEMS	7	0.736	IEEE ACCESS	7	0.797
19	TRANSPORTATION RESEARCH PART D TRANSPORT AND ENVIRONMENT	7	0.736	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	7	0.797
20	BEHAVIOURAL PROCESSES	6	0.631	INTERNATIONAL JOURNAL OF PRODUCTION ECONOMICS	7	0.797
21	ENGINEERING CONSTRUCTION AND ARCHITECTURAL MANAGEMENT	6	0.631	JOURNAL OF INTELLIGENT MANUFACTURING	7	0.797
22	JOURNAL OF CLEANER PRODUCTION	6	0.631	MATHEMATICAL PROBLEMS IN ENGINEERING	7	0.797
23	JOURNAL OF FORECASTING	6	0.631	PLoS ONE	7	0.797
24	MATHEMATICS	6	0.631	TRANSPORTATION RESEARCH PART B METHODOLOGICAL	7	0.797
25	PHYSICA A STATISTICAL MECHANICS AND ITS APPLICATIONS	6	0.631	ANNALS OF OPERATIONS RESEARCH	6	0.683

NP = number of publications.

3.2.9. NN Articles Productivity Analysis Using Lotka's Law

The procedures for certifying the validity of our results were as follows:

1. Gather data from SSCI database;
2. Calculate the distribution of author productivity in NN research;
3. Use the Lotka's law formulae to calculate the n and c values;
4. Apply the Kolmogorov–Smirnov test to verify whether the results complied with Lotka's law.

The Distribution of Author Productivity in NN Research

We obtained the author data for 951 NN articles from the SSCI database. Then, we aggregated and accumulated all of the author data to calculate the total number of authors who had published NN research (Table 7). We found that there was a total of 951 articles from 2950 authors, with an average of 3.1 (2950/951) authors per article.

Table 7. An analysis of author productivity in NN research.

NP	Author(s)	NP × Author	Accumulated Record	Accumulated Record (%)	Accumulated Author (s)	Accumulated Author(s) (%)
12	1	12	12	0.36%	1	0.03%
11	0	0	12	0.36%	1	0.03%
10	0	0	12	0.36%	1	0.03%
9	1	9	21	0.63%	2	0.07%
8	1	8	29	0.87%	3	0.10%
7	3	21	50	1.49%	6	0.20%
6	2	12	62	1.85%	8	0.27%
5	6	30	92	2.75%	14	0.47%
4	12	48	140	4.18%	26	0.88%
3	42	126	266	7.95%	68	2.31%
2	200	400	666	19.89%	268	9.08%
1	2682	2682	3348	100.00%	2950	100.00%

NP = number of publications.

The Use of the Lotka's Law Formula to Obtain the n Value

Using the data presented in Table 5 and the Lotka's law formula in Equation (1), we obtained the n value:

$$\boldsymbol{n} = \frac{\boldsymbol{N}\sum \boldsymbol{XY} - \sum \boldsymbol{X} \sum \boldsymbol{Y}}{\boldsymbol{N}\sum \boldsymbol{x}^2 - \left(\sum \boldsymbol{x}\right)^2} \tag{1}$$

Using the data presented in Table 8 and n = 12, we obtained the value of n = −3.313028132:

$$n = \frac{12(3.298263) - (86.70113095)}{12(7.464290) - (75.348250)}$$

The Use of the Lotka's Law Formula to Obtain the c Value

Then, we also used the Lotka's law formula in Equation (2) to obtain the c value:

$$\mathbf{c} = \frac{1}{\sum_1^{p-1} \frac{1}{x^n} + \frac{1}{(n-1)\left(p^{n-1}\right)} + \frac{1}{2p^n} + \frac{n}{24(p-1)^{n+1}}} \tag{2}$$

p = 20, x = 1, 2, 3, 4, 5, 6,7,8,9,10,11 and 12.
Using the above data, we obtain the value of c = 0.868637581:

$$c = \frac{1}{\sum_1^{20-1} \frac{1}{x^{-3.313028132}} + \frac{1}{(-3.313028132-1)\left(20^{-3.313028132-1}\right)} + \frac{1}{2*20^{-3.313028132}} + \frac{-3.313028132}{24(20-1)^{-3.313028132+1}}}$$

Finally, we substituted $n = -3.313028132$ and $c = 0.868637581$ into Equation (3) to obtain:

$$f(x) = \frac{c}{x^{|n|}} = \frac{0.868637581}{X^{3.313028132}} \quad (3)$$

Table 8. The calculation of the exponent n for NN publications.

NP (x)	Author (y)	X = log(x)	Y = log(y)	XY	XX
1	2682	0.00	3.43	0.00	0.00
2	200	0.30	2.30	0.69	0.09
3	42	0.48	1.62	0.77	0.23
4	12	0.60	1.08	0.65	0.36
5	6	0.70	0.78	0.54	0.49
6	2	0.78	0.30	0.23	0.61
7	3	0.85	0.48	0.40	0.71
8	1	0.90	0.00	0.00	0.82
9	1	0.95	0.00	0.00	0.91
10	0	1.00	–	–	1.00
11	0	1.04	–	–	1.08
12	1	1.08	0.00	0.00	1.16
Total	2950	8.68	9.99	3.30	7.46

NP = number of publications; x = number of publications; y = author; X = logarithm of x; Y = logarithm of y.

From the data presented in Table 7, we calculated that the proportion of authors with one NN article was 90.92%, which was close to the c value (86.86%) that was obtained using Lotka's law. Moreover, we applied the least squares method to calculate the n and c values and establish whether the results matched those obtained using Lotka's law [72,73].

On the basis of Pao's (1989) indication, the absolute value of n should be between 1.2 and 3.8. We found that the absolute value of n = 3.313028132 did match the results obtained using Lotka's law [70]. The distribution trend is shown in Figure 4.

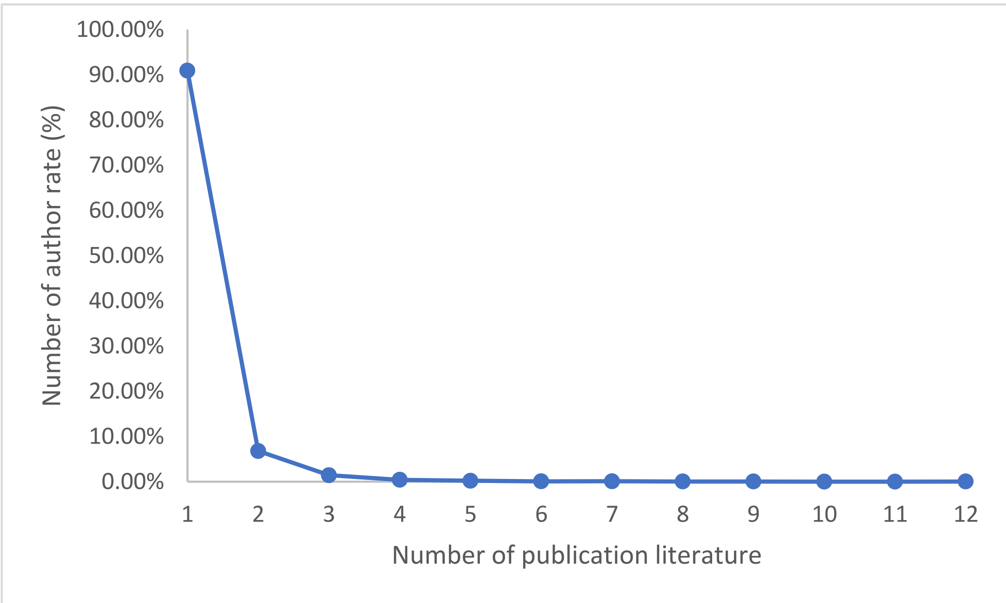

Figure 4. The author productivity in NN research.

The Application of the Kolmogorov–Smirnov Test to Verify Whether the Results Complied with Lotka's Law

Using the Lotka's law equations, we calculated the following values:

$$n = -3.313028132 \text{ and } c = 0.868637581.$$

We found that the results for the distribution of author productivity in NN research complied with Lotka's law (Figure 4). We then used the n and c values to calculate the expected and accumulaton numbers of authors and applied the Kolmogorov–Smirnov test to evaluate whether the calculated values matched the theoretical values obtained using Lotka's law. We also calculated the Dmax value presented in Table 9 as follows:

$$\text{Dmax} = \text{Absolute value of } (\text{Fo}(x) - \text{Sn}(x))$$

Table 9. The results of the Kolmogorov–Smirnov test for NN research.

NP	Observation by Author(s)	Accumulated Value Sn(x)	Expected Value by Author(s)	Accumulated Value Fo(x)	ABS Value Fo(x) − Sn(x) Dmax
1	0.90915	0.90915	0.88076	0.88076	0.028390763
2	0.06780	0.97695	0.08183	0.96259	0.014357179
3	0.01424	0.99119	0.02038	0.98297	0.008211635
4	0.00407	0.99525	0.00760	0.99058	0.004676717
5	0.00203	0.99729	0.00354	0.99412	0.003172625
6	0.00068	0.99797	0.00189	0.99601	0.001956854
7	0.00102	0.99898	0.00112	0.99713	0.001857395
8	0.00034	0.99932	0.00071	0.99783	0.001490022
9	0.00034	0.99966	0.00047	0.99830	0.0013573
10	0.00000	0.99966	0.00033	0.99863	0.001028591
11	0.00000	0.99966	0.00024	0.99887	0.0007915
12	0.00034	1.00000	0.00018	0.99905	0.000954539

NP = number of publications; Sn(x) = observed cumulative frequency; Fo(x) = theoretical cumulative frequency; D = maximum deviation.

On the basis of the Kolmogorov–Smirnov test, the threshold value was set as follows:

$$1.63/\sqrt{2950} = 0.030010733$$

We found that the calculated Dmax values were much smaller than the threshold value, which meant that the distribution of author productivity in NN research complied with Lotka's law.

3.2.10. GA Articles Productivity Analysis Using Lotka's Law

The procedures for certifying the validity of our results were as follows:

1. Gather data from the SSCI database;
2. Calculate the distribution of author productivity in GA research;
3. Use the Lotka's law formulae to calculate the n and c value;
4. Apply the Kolmogorov –Smirnov test to verify whether the results complied with Lotka's law.

The Distribution of Author Productivity in GA Research

We obtained the author data for 878 GA articles from the SSCI database. Then, we aggregated and accumulated all of the author data to calculate the total number of authors who had published GA research (Table 10). We found that there was a total of 878 articles from 2430 authors, with an average of 2.77 (2430/878) authors per article.

Table 10. An analysis of author productivity in GA research.

NP	Author(s)	NP × Author	Accumulated Record	Accumulated Record (%)	Accumulated Author (s)	Accumulated Author(s) (%)
7	1	7	7	0.25%	1	0.04%
6	6	36	43	1.54%	7	0.29%
5	4	20	63	2.26%	11	0.45%
4	10	40	103	3.69%	21	0.86%
3	47	141	244	8.74%	68	2.80%
2	187	374	618	22.13%	255	10.49%
1	2175	2175	2793	100.00%	2430	100.00%

NP = number of publications.

The Use of the Lotka's Law Formula to Obtain The n Value

Using the data presented in Tables 10 and 11 and N = 7, we obtained the value of $n = -3.768656463$:

$$n = \frac{7(3.110087) - (35.77143977)}{7(2.489009) - (13.707992)}$$

Table 11. The calculation of the exponent n for GAs.

NP (x)	Author (y)	X = log(x)	Y = log(y)	XY	XX
1	2175	0.00	3.34	0.00	0.00
2	187	0.30	2.27	0.68	0.09
3	47	0.48	1.67	0.80	0.23
4	10	0.60	1.00	0.60	0.36
5	4	0.70	0.60	0.42	0.49
6	6	0.78	0.78	0.61	0.61
7	1	0.85	0.00	0.00	0.71
Total	2430	3.70	9.66	3.11	2.49

NP = number of publications; x = number of publications; y = author; X = logarithm of x; Y = logarithm of y.

The Use of the Lotka's Law Formula to Obtain the c Value

$n = -3.768656463$, $p = 20$, $x = 1, 2, 3, 4, 5, 6, 7$

Using the above data, we obtained the value of c = 0.908883846:

$$\mathrm{c} = \frac{1}{\sum_1^{20-1} \frac{1}{x^{-3.768656463}} + \frac{1}{(-3.768656463-1)\left(20^{-3.768656463-1}\right)} + \frac{1}{2*20^{-3.768656463}} + \frac{-3.768656463}{24(20-1)^{-3.768656463+1}}}$$

Finally, we substituted $n = -3.768656463$ and c = 0.909490628 into the below equation to obtain:

$$\mathrm{f}(x) = \frac{0.909490628}{X^{3.768656463}}$$

From the data presented in Table 10, we found that the proportion of authors with one GA article was 89.51%, which was close to the c value (90.95%) that was obtained using Lotka's law. Moreover, we applied the least squares method to calculate the n and c values and establish whether the result matched those obtained using Lotka's law [72,73].

On the basis of Pao's (1989) indication, the absolute value of n should be between 1.2 and 3.8. We found that the absolute value of $n = -3.768656463$ did match the results obtained using Lotka's law [70]. The distribution trend is shown in Figure 5.

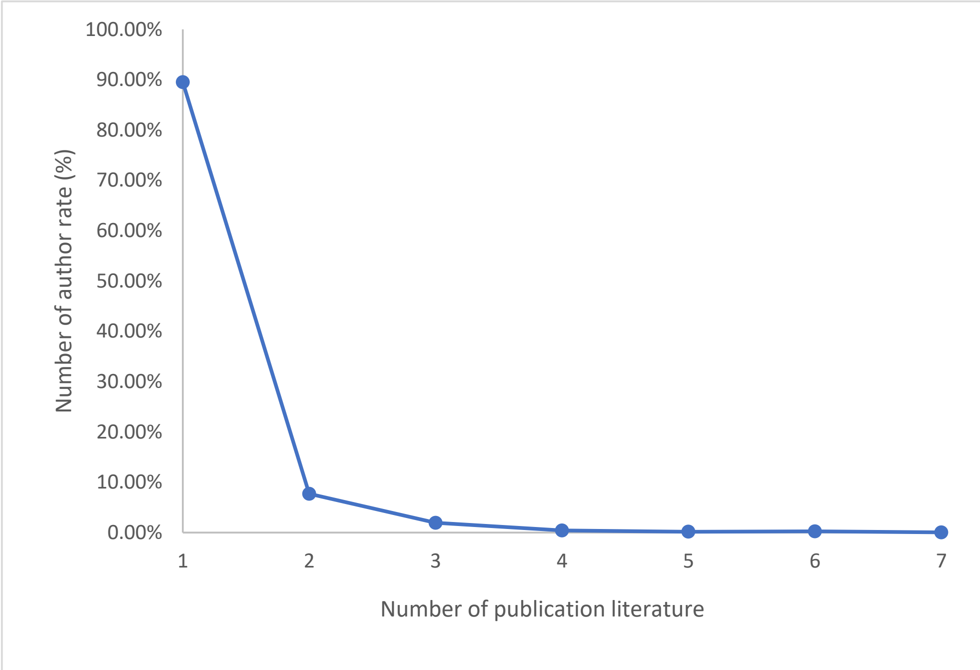

Figure 5. The author productivity in GA research.

The Application of the Kolmogorov–Smirnov Test to Verify Whether the Results Complied with Lotka's Law

Using the Lotka's law equations, we calculated the following values:

$$n = -3.768656463 \text{ and } c = 0.909490628.$$

We found that the results for the distribution of author productivity in GA research complied with Lotka's law (Figure 5). We then used the n and c value to calculate the expected and accumulation numbers of authors and applied the Kolmogorov–Smirnov test to evaluate whether the calculated values matched the theoretical values obtained using Lotka's law. We also calculated the Dmax value presented in Table 12 as follows:

$$\text{Dmax} = \text{Absolute value of } (\text{Fo}(x) - \text{Sn}(x))$$

Table 12. The results of the Kolmogorov–Smirnov test for GA research.

NP	Observation by Author(s)	Accumulated Value Sn(x)	Expected Value by Author(s)	Accumulated Value Fo(x)	ABS Value Fo(x) − Sn(x) Dmax
1	0.89506	0.89506	0.90949	0.90949	0.0144289
2	0.07695	0.97202	0.06673	0.97622	0.004203931
3	0.01934	0.99136	0.01448	0.99070	0.000660181
4	0.00412	0.99547	0.00490	0.99559	0.000120588
5	0.00165	0.99712	0.00211	0.99771	0.00058614
6	0.00247	0.99959	0.00106	0.99877	0.000820778
7	0.00041	1.00000	0.00059	0.99936	0.000638127

NP = number of publications; Sn(x) = observed cumulative frequency; Fo(x) = theoretical cumulative frequency; D = maximum deviation.

On the basis of the Kolmogorov–Smirnov test, the threshold value was set as follows:

$$1.63/\sqrt{2430} = 0.033066214$$

We found that the calculated Dmax values were much smaller than the threshold value, which meant that the distribution of author productivity in GA research complied with Lotka's law.

3.2.11. Advanced H-Index Analysis of NN and GA Research

The h-index is a useful index that characterizes the scientific output of researchers. Hirsch believes that the h-index can solve the shortcomings of measuring an author's research results using the number of published papers or citation count by synthesizing a new evaluation method that integrates quality and quantity [75]. For example, when the h-index value of researcher A is greater than that of researcher B, it means that the overall quality of the papers from researcher A is better than that of papers from researcher B. The h-index can also be applied to measure the contributions of institutions and countries. H-index value can be calculated using data from the SSCI database on the Web of Science platform.

The H-Index Analysis of Authors of NN and GA Publications

From Table 13, it can be seen that Azadeh had the highest h-index value in GA research (10) and Resende had the highest h-index value in NN research (6). We also found that the average h-index value of authors of GA publications was higher than the average h-index value of authors of NN publications, as shown in Table 13.

Table 13. The top 10 authors in our h-index analysis (from 2002 to 2021, SSCI).

Ranking	Neural Networks		Genetic Algorithm	
	Author	**H-Index**	**Author**	**H-Index**
1	Resende, Mauricio G. C.	6	Azadeh, Ali	10
2	Niaki, Seyed Taghi Akhavan	5	OOI, Keng-Boon	8
3	Pendharkar, Parag C.	5	Saberi, Morteza	7
4	Oh, Kyong Joo	4	Ghiassi, M.	7
5	Ruiz, Rubén	4	Leong, Lai-Ying L.Y.	6
6	Chung, Sai-Ho	4	Tan Wei Han, Garry	5
7	Azadeh, Ali	4	Maurelli, Guido	2
8	Huang, Bo	4	Dawson, Michael RW	2
9	Ceylan, Halim	4	Palmer, Alfonso	2
10	Dung-Ying Lin	3	Buscema, Paolo Massimo	2

The H-Index Analysis of Institutions Producing NN and GA Publications

From Table 14, it can be seen that the University of Tehran was the institution with the highest h-index value in NN research and the Islamic Azad University was the institution with the highest h-index value in GA research. Both are institutions in Iran and their research contributions were the greatest. The Islamic Azad University, the Iran University of Science and Technology, the Sharif University of Technology, and the University of Tehran are also all institutions in Iran, meaning that Iranian institutions contributed the most NN and GA publications, as shown in Table 14. The Universiti Malaya and the Hong Kong Polytech University had the second highest h-index values in NN and GA research, respectively. The Pennsylvania State System of Higher Education had an h-index value of 9 for both NN and GA research. Our results also showed that the Universitat Politècnica de València, the State University System of Florida, and the Indian Institutes of Technology are catching up in terms of their research contributions.

Table 14. The top 10 institutions in our h-index analysis (from 2002 to 2021, SSCI).

Ranking	Neural Networks		Genetic Algorithm	
	Institution	**H-Index**	**Institution**	**H-Index**
1	UNIVERSITY OF TEHRAN	12	ISLAMIC AZAD UNIVERSITY	10
2	UNIVERSITI MALAYA	12	HONG KONG POLYTECHNIC UNIVERSITY	9
3	ISLAMIC AZAD UNIVERSITY	10	PENNSYLVANIA COMMONWEALTH SYSTEM OF HIGHER EDUCATION PCSHE	9
4	PENNSYLVANIA COMMONWEALTH SYSTEM OF HIGHER EDUCATION PCSHE	9	UNIVERSITAT POLITECNICA DE VALENCIA	9
5	STATE UNIVERSITY SYSTEM OF FLORIDA	8	INDIAN INSTITUTE OF TECHNOLOGY SYSTEM IIT SYSTEM	9
6	IRAN UNIVERSITY SCIENCE TECHNOLOGY	8	IRAN UNIVERSITY SCIENCE TECHNOLOGY	8
7	EGYPTIAN KNOWLEDGE BANK EKB	7	NATIONAL INSTITUTE OF TECHNOLOGY NIT SYSTEM	8
8	INDIAN INSTITUTE OF TECHNOLOGY SYSTEM IIT SYSTEM	7	SHARIF UNIVERSITY OF TECHNOLOGY	8
9	UCSI UNIVERSITY	7	UNIVERSITY OF TEHRAN	8
10	CHINESE ACADEMY OF SCIENCES	6	BEIJING JIAOTONG UNIVERSITY	6

The H-Index Analysis of the Countries Producing NN and GA Publications

From Table 15, it can be seen that the USA contributed the most to NN and GA research as it had the highest h-index values in NN and GA research and produced the second highest quantity of NN and GA publications. In contrast, China had the second highest h-index values in NN and GA research and produced the highest quantity of NN and GA publications. Other countries, including Iran, Taiwan, Turkey, South Korea, and Malaysia, were smaller contributors, but our results showed that they are catching up quickly and becoming potential contributors to NN and GA research.

Table 15. The top 10 countries in our h-index analysis (from 2002 to 2021, SSCI).

Ranking	Neural Networks		Genetic Algorithm	
	Countries/Territories	**H-Index**	**Countries/Territories**	**H-Index**
1	USA	42	USA	40
2	PEOPLES R CHINA	32	PEOPLES R CHINA	37
3	IRAN	25	TAIWAN	26
4	TURKEY	21	SOUTH KOREA	22
5	MALAYSIA	21	IRAN	21
6	TAIWAN	19	INDIA	19
7	CANADA	16	SPAIN	18
8	SPAIN	15	ENGLAND	18
9	INDIA	15	TURKEY	16
10	AUSTRALIA	15	CANADA	15

4. Conclusions

We used a bibliometric analytical technique to examine NN and GA publications in SSCI journals from 2002 to 2021. We found 951 NN publications and 878 GA publications in total. We then analyzed these publications and obtained our final research results by evaluating the following eight criteria: (1) publication year; (2) citation count; (3) country/territory; (4) institution name; (5) document type; (6) language; (7) subject area; and (8) source title. Furthermore, we also applied the Kolmogorov–Smirnov test to verify whether the distributions of author productivity in NN and GA research complied with Lotka's law and advanced h-index analysis. In sum, this paper provides the following findings and implications:

First, according to our analysis by publication year, we found that the number of NN publications has grown faster than the number of GA publications and NN research has become much more popular. Based on the ascending trends of NN and GA publications, we predict that research in both areas will keep growing continuously. We also predict that

NNs and GAs will continue to be important in artificial intelligence research for quite some time due to the third boom in AI development. Second, according to our analysis of the trends of NN and GA citations, we observed upward trends for NN and GA publications and we predict that these trends will continue in the future, as long as the AI industry is still booming.

Third, on the basis of our countries/territories analysis of NN and GA publications, we found that China and the USA contribute the most to NN and GA research and observed the significance of AI within the context of the USA–China confrontation. Iran was in third place for NN publications and Taiwan was in third place for GA publications. We also conclude that contributions from Turkey, South Korea, and Spain are growing fast and they are becoming potential competitors in NN and GA research. Fourth, according to our research institution analysis of NN and GA publications, the top NN research institution was the University of Tehran and the top GA research institution was the Islamic Azad University. Both are institutions in Iran and both published over 20 articles from 2002 to 2021. The second-place institution in NN research was the Universiti Malaya and Hong Kong Polytech University. The third-place institutions in NN and GA research were the Islamic Azad University and the Iran University of Science and Technology, respectively. Furthermore, we also observed that Iran was the most productive country for NN and GA research.

Fifth, from our analysis of document types in NN and GA research, we found that articles are still the major and most popular document type for NN and GA research publications. Sixth, from our analysis of the language used in NN and GA research and as English is the predominant scientific language that is most widely used among scientists worldwide, we concluded that English was still the number one language used in NN and GA research publications. Seventh, from our analysis, we found that computer science and engineering were the major domains of NN and GA research and that environmental sciences ecology research is catching up due to the rapid development of ESG. Furthermore, we also identified many other important and potential research domains for NN and GA publications, including business economies, mathematics, psychology, transportation, information science, library science, energy, etc. We predict that these research areas will become more popular in the future.

Eighth, we discovered that the top three NN research source titles were *Sustainability*, *Expert Systems with Applications*, and the *International Journal of Environmental Research and Public Health*, *while* the top three GA research source titles were *Expert Systems with Applications*, *Sustainability*, and the *Journal of Operation Research Society*. Additionally, there were many other popular research sources titles for NN and GA publications, including *Neural Computing Applications*, *Energy Policy*, *PLoS ONE*, *Applied Soft Computing*, *Computational Economics*, *Computers Industrial Engineering*, etc. We predict that these source titles will become more attractive in the near future.

Finally, we performed an advanced h-index analyses of NN and GA publications using different criteria, such as author, institution, and country to measure researcher contributions. We obtained the following results:

- The average h-index value of GA publications was higher than the average h-index value of NN publications, as shown in Table 13.
- Iranian institutions contributed the most NN and GA publications, as shown in Table 14.
- The USA contributed the most to NN and GA research, with highest h-index value and the second highest quantity of NN and GA publications. In contrast, China had the second highest h-index values in NN and GA research but produced the second highest quantity of NN and GA publications.

We hope that our bibliometric analysis results will serve as a roadmap for other NN and GA researchers and act as guidelines for further studies. In the future, it is suggested to conduct similar research based on more innovative hybrid classical algorithm models and new bibliometrics methods, such as y-index analysis, frequent keywords analysis, the "life" of references cited in journals, and other advanced data-analysis techniques [75,76].

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