Covenant Journal of Informatics & Communication Technology. Vol. 10 No. 2, Dec, 2022
ISSN: ***print*** **2354 – 3566** ***electronics*** **2354 – 3507 DOI:**

An Open Access Journal Available Online

Scientometric Analysis of Optimisation and Machine Learning Publications

David Opeoluwa Oyewola[1], Emmanuel Gbenga Dada [2], K. A. Al-Mustapha[3], Rowland Ogunrinde[4], E. E, Daniel[5]

[1] Department of Mathematics and Computer Science, Federal University of Kashere, Gombe, Nigeria.
[1] davidoyewole@fukashere.edu.ng
[2] Department of Mathematical Sciences, University of Maiduguri, Maiduguri, Nigeria.
[2] gbengadada@unimaid.edu.ng
[3] Department of Mathematical Sciences, Baze University Abuja, Nigeria.
[3] kuluwa.al-mustapha@bazeuniversity.edu.ng
[4] Department of Mathematical Sciences, Augustine University, Ilara-Epe, Nigeria.
[4] rowland.ogunrinde@augustineuniversity.edu.ng
[5] Department of Mathematics and Computer Science, Federal University of Kashere, Gombe, Nigeria.
emmytetra@yahoo.com

Received: 11.08.2022 Accepted: 15.11.2022

Publication: December 2022

***Abstract*— Introduction:** Optimisation is an important aspect of machine learning because it helps improve accuracy and reduce errors in the model's predictions.
Purpose: The purpose of this research is to identify the global structure of optimization and machine learning. The work specifically looks at the collaborative network of countries in these fields, the top 20 authors in terms of production from 2015–2021, and the co-citation network of articles.
Methodology: In this study, co-word analysis and social network analysis were used to conduct a descriptive study based on the scientometric approach and the content analysis method. In this research, around 17,500 articles on optimization and machine learning published between 2015 and 2021 were extracted. An ANOVA was performed to evaluate whether there was a significant difference between betweenness, closeness, and pagerank. The Dimensions database was utilised for the investigation without language constraints. Moreover, Bibliometrix was used for calculation and visualization.
Findings: The results revealed a substantial difference between betweenness, proximity, and pagerank, indicating that this research has the potential to bring vital insights into future optimization and machine learning research.

***Keywords/Index Terms*—** Scientometrics, Optimization, Machine Learning, ANOVA, Bibliometrix

1. Introduction

In Operation Research (OR), the objective is to find the best decision or solution to a problem, considering the available data and constraints. In Machine Learning (ML), the focus is on creating models that can learn from data and make predictions or decisions based on that learning. Both OR and ML have applications in various fields, including finance, healthcare, and transportation. However, there is a growing interest in combining the two areas in order to improve the accuracy and efficiency of decision-making and problem-solving. OR and ML can be integrated in various ways. For example, OR techniques can be used to optimize the parameters of a ML model, or to develop algorithms that can learn from data and make predictions. Similarly, ML techniques can be used to improve the performance of OR algorithms, or to develop models that can learn from data and make decisions. The combination of OR and ML offers many benefits, including the ability to handle complex problems with uncertainty, the ability to make more accurate predictions and decisions, and the ability to improve the efficiency of computational algorithms. However, the integration of these two areas also poses challenges, such as the need for advanced mathematical and computational skills, and the need to develop algorithms that can handle large and complex datasets. However, OR and ML are two important areas of research that have the potential to improve decision-making and problem-solving in various fields. By combining these two areas, researchers can develop more effective and efficient methods for dealing with complex problems with uncertainty (Taravera, 2020). Operation Research (OR) courses at some universities have started incorporating quantitative computational methods from machine learning and AI to enhance their applications in fields like healthcare, forecasting, and optimization (Chui, 2018). However, one challenge educators face when using ML techniques in OR courses is the dearth of computational understanding among undergraduate students. Thankfully, there are computer programming languages like Python, Matlab and R provide an accessible way for students with minimal computer knowledge to use these programs thanks to the availability of user-friendly toolboxes and packages (Luna, 2020).

Operations research (OR) and machine learning (ML) are often considered separate and distinct approaches to data-driven decision-making within the broader field of data science. OR is often referred to as predictive analysis, while ML is referred to as prescriptive analysis (Saclay, 2018). While operations research is often viewed as a prescriptive form of analysis that does not provide immediate benefits from the data it generates, machine learning is seen as a predictive analysis that often offers quick wins from the data it generates. In recent decades, the scientific community has significantly increased its use of operations research and machine learning. Numerous significant developments have boosted the subject, which today has hundreds of researchers as a result of the formation of organisations like the Operations Research Society of America, the Operational Research Society of the United Kingdom, and the Institute of Management Sciences. Traditional periodicals in the area that are now essential for communicating new research have received assistance from these organizations.

The Operational Research Quarterly, which eventually became the Journal of the Operational Research Society, Operations Research, and Machine Learning are a few examples. Through combined international conferences and cooperation, these and other operations research associations have collaborated. The establishment of the International Federation of Operational Research Societies in 1959 brought together the Operational Research Society and the French Operational Research Society. IFORS now has over 30,000 members from 48 national organisations. Regional organisations have also gathered scholars from other continents, such as the Association of European Operational Research Societies, created in 1975. The Association of North American Operations Research Societies, the Latin American Ibero-American Association on Operations Research, and the Association of Asian-Pacific Operational Research Societies are just a few of the regional organisations that have been founded throughout the world. The 1995 merger of ORSA and TIMS, which resulted in the creation of the Institute for Operations Research and Management Sciences, was another important development in the area. Currently, INFORMS supports thirteen top OR-MS publications, including some of the most prestigious journals in the discipline, and has about 10,000 individual members (Kraus, 2019). This work's major contributions include:

1. A review of recent developments in ML models, global structural networks, and their use to categorize, standardize, and classify relevant papers was presented.
2. Using scientometrics to investigate several ML research areas that have grabbed the interest of the academic community.
3. Analyse the worldwide structure of machine learning to identify bibliographic coupling, research institution collaboration, country co-authorship networks, and source coupling; and
4. A total of 17,500 papers on optimization and machine learning published between 2015 and 2021 were used on the software tools Bibliometrix and VOSviewer (version 1.6.16) to generate and visualise a structural map of source coupling networks in journals, books, or other publications.

The structure of this work has been enhanced by following the format specified in Misra (2021). The remainder of this paper is structured as follows: Section 2 discussed the related works. Section 3 is the methodology. And section 4 presents the results and discussions.

2. Related Works

When paired with operations research approaches, the use of artificial intelligence (AI) has the potential to create major breakthroughs. In their research, they look at existing techniques for employing AI to solve optimization challenges, with a particular focus on how they are used in marine logistics. The purpose is to present an overview of current advancements and look into their prospective applications in this field (Dornemann, 2020). There are several planning difficulties in marine logistics that may be classified according to their applicability. There are strategic design concerns for container liner networks at sea, such as selecting ports and routes and making operational decisions concerning vessel speed (Meng, 2014). OR is used to coordinate operations, procedures, and activities in organisations such as businesses and military institutions (Hillier, 2010). It entails the creation and implementation of quantitative models and decision-support tools (Kandiller, 2007). (Eiselt, 2010). The purpose of OR is to find the best answer to a planning problem, such as transportation planning or manpower deployment planning (Lieberman, 2010). In contrast, machine learning is used in computer jobs where inventing and implementing explicit methods that perform effectively is difficult or prohibitive. It is concerned with performing a job using a limited collection of data known as "training data" (Bengio, 2018). There are several learning techniques used in machine learning. In supervised learning, input and target pairs are used as training data to develop a function that generates outputs that are as near to the target as feasible for each input. The measure of difference between the output and the objective can be chosen based on the job while solving optimization issues to address this learning process (Prouvost, 2018). Understanding the distinctions and similarities between OR and machine learning is essential for understanding how AI, primarily machine learning, may be utilised to improve OR strategies for addressing optimization issues. OR and machine learning both employ iterative approaches to address real issues, and optimization problems in OR may be expressed as a restricted maximisation or minimisation problem, with the objective function defining the solution's quality (Lodi, 2018).

In recent years, machine learning has grown fast, yielding several theoretical advances and significant applications in a variety of industries. Optimization, a critical component of machine learning, has received a lot of attention from academics. Optimization approaches in machine learning encounter growing hurdles as data quantities expand rapidly and model complexity grows. There has been a lot of study in machine learning for solving optimization problems and developing optimization algorithms. It is critical to do a thorough assessment and summary of optimization methods from the standpoint of machine learning, since this can give direction for both optimization and machine learning research. The four main categories of machine learning algorithms are: supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning. These categories can be further subdivided based on the issue to be addressed and the modelling goal. Supervised learning is further subdivided into classification difficulties such as sentences (Kim, 2014) and images (Bazi, 2010), as well as regression problems (Ciresan, 2012). Clustering and dimension reduction are two categories of unsupervised learning (Ding, 2002; Hartigan, 1979). An input is mapped to an output using input-output pairs in supervised learning, a type of machine learning. Because learning is guided by tagged observations, supervised learning is distinguished from unsupervised learning by the presence of labelled response variables. In supervised learning, datasets are trained on training data in order to create a model, which is then applied to classify fresh observations from the testing data. The input variables—also referred to as features—in the training set have an impact on the predicted variable's accuracy. While the supervised learning model will use the output variable, or label class, to classify new observations, they might be both quantitative and qualitative (Hinton, 2010). Semi-supervised learning, a technique that straddles the supervised and unsupervised learning spectrums, trains models using both labelled and unlabeled data. It is capable of performing a variety of tasks, including classification (Guillaumin, 2010), regression (Zhou, 2005), clustering (Kulis, 2009), and dimensionality reduction (Chen, 2017). A learning model called support vector machines (SVM) can solve binary classification issues and only needs a portion of the training data to be labeled. Unsupervised learning is a sort of machine learning where no labels or scores have been applied to the training data in advance (Stuart, 2010; Geoffrey, 1999). Unsupervised learning algorithms, as a result, must first discover any naturally existing patterns in the training data set. Clustering methods (Hartigan, 1979) separate a bunch of samples into numerous clusters, ensuring that the differences between samples within the same cluster are as small as feasible and the differences between samples in different clusters are as large as possible. Clustering algorithms have evolved into an effective tool for exploratory data analysis. A cluster is defined as a collection of things that are more similar to one another than to objects outside the collection. However, there is dispute over the appropriate similarity metric for clustering. Multiple measures have been proposed for quantifying similarity, such as Euclidean distance and density in data space, making clustering a multi-objective optimization problem. In this study, several clustering algorithms are examined from a theoretical standpoint to comprehend their applicability for large data sets, and are evaluated against fake benchmarks to show their advantages and disadvantages (Archana, 2018). As a result, unsupervised learning algorithms must first self-discover any naturally existing patterns in that training data set. Clustering algorithms (Hartigan, 1979) separate a bunch of samples into numerous clusters, ensuring that the differences between samples within the same cluster are as small as feasible and samples within clusters are as dissimilar as possible. Clustering algorithms have evolved as meta-learning tools for undertaking exploratory data analysis. A cluster is defined as a group of things that are more similar to one another than to objects that are not in the same set. However, there is uncertainty about the best similarity metric for clustering. Multiple metrics for assessing similarity, such as Euclidean distance and density in data space, have been presented, making clustering a multi-objective optimization problem. In this study, multiple clustering algorithms are explored from a theoretical perspective to understand their significance in the context of enormous data sets, and experimentally, they have been evaluated on fake benchmarks to highlight their strengths and drawbacks (Archana, 2018; Archana, 2018). According to Neerurkar (2018), clustering is a meta-learning strategy that delivers insights into data in a variety of disciplines, including market research, e-commerce, social network analysis, and search result aggregation. There are several techniques for arranging data into clusters, but there is no universal answer to all issues. There is no agreement on the "best" algorithm because each one is created with particular assumptions and has its own biases. These algorithms are classified as partitioning-based, hierarchical, density-based, grid-based, message passing-based, neural network-based, probabilistic, and generative model-based. However, because clustering is an NP-hard grouping problem, present algorithms rely on approximation techniques or heuristics to narrow the search space and discover the best answer. There are no widely accepted objective criteria for clustering accuracy or validity, and each technique has its own set of benefits and drawbacks for tackling the difficult challenge of unsupervised clustering (Scholkopf, 2009; Castro, 2002). Data analytics has grown rapidly in the field of operations management in recent years. The increased availability of data, along with advances in machine learning, has resulted in a huge body of research on this topic that employs machine learning approaches to examine how organisations should function. This paper looks at how several machine learning approaches, such as supervised learning, unsupervised learning, and reinforcement learning, are used in various areas of operations management. It demonstrates how supervised and unsupervised learning influence operations management research in descriptive and prescriptive analyses, as well as how different types of reinforcement learning are used in various operational decision situations. Finally, it discusses promising future paths at the crossroads of machine learning and operations management.

To handle the virtual machine (VM) scheduling problem, the author (Rana et al., 2021) suggested a hybrid multi-objective whale optimization algorithm-based differential evolution (M-WODE) approach. In this study, a differential evolution (DE) approach is used to replace the randomly generated solution provided by the Whale Optimization Algorithm (WOA). It was used to ensure variety in the solution and boost M-WODE's local search. Furthermore, the DE approach is applied to the Pareto front generated by the WOA in order to avoid local optima entrapment difficulties. In most cases, the experimental results showed that the proposed M-WODE algorithm outperformed earlier algorithms in terms of time complexity and cost trade-off. Crawford et al. (2017) used a binary version of the Teaching-Learning-Based Optimization (TLBO) method to solve the set covering problem with two phases known as teacher and learner, imitating the behaviour in a classroom. On 65 benchmark instances, the suggested approach was evaluated. The results suggest that it is capable of producing competitive solutions.

To choose the ideal sensitization method, Okewu et al. (2017) used a stochastic optimization problem and a metaheuristic search technique. The authors conducted a study of the available literature, gathered requirements, used Universal Modeling Language (UML) to model the suggested solution, and then created a prototype. A web-based, multi-tiered e-Green computing system is the suggested remedy; it instructs computer users in cutting-edge methods for handling computers and peripherals in an ecologically beneficial manner. They discovered that a real-time web-based interactive forum like this increases people's awareness of the negative effects their computer use has on the environment. This is in addition to piquing their interest in environmental concerns. By doing this, he voluntarily contributes to the effort to reverse environmental damage in his sphere of influence.

An ant colony optimization algorithm paradigm was created by Crawford et al. (2015), utilising the Hyper-Cube framework to address the software project scheduling problem. This NP-hard issue involves distributing jobs to workers in a way that reduces the project's time and overall cost. The limitations of the challenge and the order of tasks must be satisfied by this assignment. This method uses the Hyper-Cube framework to intentionally create a multidimensional space where the behaviour of the ants may be managed. This enables them to manage the search and space exploration independently in order to find motivating solutions. Dada et al. (2021) also used ensemble machine learning for software defect prediction.

To address the challenge of recognising early-stage breast cancer, Ogundokun et al. (2022) present a medical Internet of Things (IoT)-based diagnostic system that competently distinguishes malignant from benign individuals in an IoT environment. For malignant vs. benign classification, the artificial neural network (ANN) and convolutional neural network (CNN) with hyperparameter tuning were employed, while the support vector machine (SVM) and multilayer perceptron (MLP) were used as baseline classifiers for comparison. Hyperparameters are vital for machine learning algorithms because they directly regulate the behaviour of training algorithms and have a major impact on model performance. To improve the classification performance of the breast cancer dataset using MLP and SVM, they adopted a particle swarm optimization (PSO) feature selection strategy. Grid-based search was performed to identify the optimal setting for the CNN and ANN models' hyperparameters. The idea was tested using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. Using CNN and ANN, the suggested model achieved classification accuracy of 98.5% and 99.2%, respectively. Oyewola et al. (2016) and Dada et al. (2017) also used different ML algorithms for breast cancer detection. Convolution neural network was used by Dada et al. (2022) to detect sickle cell from image blood samples. Machine learning was also used by Oyewola and Dada (2022) to predict popularity of movies.

The ICNN-BNDOA convolutional neural network (CNN) approach, which is based on batch normalisation (BN), dropout (DO), and an adaptive moment estimation (Adam) optimizer, was proposed by Ogundokun (2002). The ICNN-BNDOA employs a sequential CNN structure with the leaky rectified linear unit (LeakyReLU) as the activation function to get over the gradient problem and hasten convergence (AF). Using the CIFAR-10 datasets as the benchmark data, the performance of the proposed system with conventional CNN (CCNN) was examined. It was found that the suggested technique displayed great recognition performance with the inclusion of BN and DO layers. With training and testing accuracy of 0.6904 and 0.6861, respectively, the statistical findings demonstrated that the suggested ICNN-BNDOA beat the CCNN. To control variations in Nigeria's population, Alfa et al. (2022) suggested using fuzzy analytics and genetic algorithms (GA). The results of the staggered GA optimizations of fuzzy analytics engines, whose rule lists were filtered to produce the best fuzzy rule list, are combined in the suggested method. Analysis revealed a 12.92% error rate compared to 17.82%, 26.95%, and 42.32% mistakes in the benchmark works. The population, birth, and death rates may be effectively managed using the insights provided by this established model, which can help government organizations, development partners, and economic planners optimise resource allocation and population well-being nationwide.

3. Methodology
One of the most common methods of scientometrics involves using citations in scientific articles and books to create connections to other works or researchers. This allows scientists to analyse citation patterns in articles, books, and journals (Avkiran et al., 2015). It is a method of evaluating and comparing researchers based on their research output, which emerged from citation analysis (Asadi et al., 2017). These bibliometric measures allow researchers to summarise their scientific output as quantitative figures that can be compared easily. They are based on objective methods, and their results can be replicated (Asadi et al., 2017). While this may seem like an advantage, Fuchs (2017) warns that the process can also be restrictive because it can omit details from citation records. Bibliometric metrics are used by many funding organisations and promotion committees to evaluate the impact of their research programs. Additionally, bibliometric measures are often used to allocate public funds to researchers. These measures count the number of citations to scientific papers and assume that major researchers and important papers will be more likely to be cited (Han et al., 2014). Bibliometric metrics are used by many funding organisations and promotion committees to evaluate the impact of their research programs. Additionally, bibliometric measures are often used to allocate public funds to researchers. These measures count the number of citations to scientific papers and assume that major researchers and important papers will be more likely to be cited (Han et al., 2014).

3.1 Degree Centrality
In a network with directed ties, degree centrality is defined as the number of links that a node has with individual nodes (Maharani et al., 2014). If the network is directed, then two separate measures of degree centrality are defined, namely, indegree and outdegree. Counting the number of ties directed to a node is called indegree, whereas counting the number of ties directed away from it is called outdegree. In such cases, the degree is equal to the sum of indegree and outdegree. The most active authors are those who have many links or ties with other authors. Consider a network of n authors. In an undirected graph, the degree centrality of an undirected graph is simply the node degree of the node that comprises the author node, denoted by *d(i)*, normalised with the maximum degree, $n-1$. The mathematical equation of an undirected graph is given in equation (1).

$$C_D(i) = \frac{d(i)}{n-1} \quad (1)$$

In this case, the author i in-links and out-links must be distinguished. Degree centrality is determined solely by the out-degree. The mathematical equation of an undirected graph is presented in equation (2).

$$C_D(i) = \frac{d_0(i)}{n-1} \quad (2)$$

3.2 Closeness Centrality
This viewpoint on centrality is determined by closeness or distance (Biscaro et al., 2014). The basic concept is that an author x_i is central if it can readily interact with all other authors. That is, it is similar to all of the other authors. As a consequence, the metric may be computed using the shortest distance. Let $d(i,j)$ to represent the smallest distance between authors i and j.
Undirected graph: The closeness centrality

$C_c(i)$ of author *i* is defined in equation (3) as:

$$C_c(i) = \frac{n-1}{\sum_{j=1}^{n} d(i,j)} \quad (3)$$

Since $n-1$ is the smallest value of the denominator, which is the sum of the shortest distances from I to all other authors, the measure value varies between 0 and 1.

A directed graph can be represented by the same equation. When determining distance, the orientations of connections or edges must be considered.

3.3 Betweenness Centrality

Betweenness measures the control *i* over other pairs of authors (Biscaro et al., 204). As a result, if *i* is involved in a large number of such interactions, *i* signify a prominent author. If two non-adjacent authors, *j* and *k*, want to engage and author *i* is on the path between them, i may have some influence over their interactions. Undirected graph: Let p_{jk}be the number of shortest routes between author *j* and *k*. The betweenness of an author *i* is defined as the number of shortest routes that pass $i(p_{jk}(i))$ normalized by the total number of shortest routes as depicted in equation (4).

$$\sum_{j<k} \frac{p_{jk}(i)}{p_{jk}} \quad (4)$$

It should be noted that there might be numerous shortest paths between *j* and *k*. We must ensure that the value range is between 0 and 1. We can normalise it using $\frac{(n-1)(n-2)}{2}$, which is the biggest value of the aforementioned quantity, such as the number of pairs of authors that do not include *i*. The mathematical equation of betweenness is defined in equation (5) as:

$$C_B(i) = \frac{2\sum_{j<k}\frac{P_{jk}(i)}{P_{jk}}}{(n-1)(n-2)} \quad (5)$$

Directed graph: Given $(n-1)(n-2)$ pairings and that a path from *j* to *k* differs from a path from *k* to *j*, the same equation may be applied, but it must be increased by 2. Similarly, p_{jk} has to take into account all possible routes.

3.4 Co-citation and Bibliographic Coupling

Another area of study that examines links is the examination of citations in academic articles. An academic article that referenced earlier work has established a relationship between the two publications. These connections (links) are used by citation analysis to conduct a number of analyses. Citation analysis comes in two flavors: co-citation and bibliographic coupling. Citation is the frequency with which two papers are cited together in other texts (Dervis, 2019). In contrast to a bibliographic coupling, which occurs when two works cite a third work in common, a co-citation occurs when at least one other work cites two other works in common (Yan et al., 2012). It suggests that there is a chance that the two works address the same subject area. Two papers are bibliographically related if they cite the same or more sources.

The number of articles that co-cite *i* and *j* is the similarity measure known as the number of papers that co-cite *i* and *j* (denoted byC_{ij}) in equation (6).

$$C_{ij} = \sum_{k=1}^{n} L_{ki}L_{kj} \quad (6)$$

C_{ij} is the quantity of publications that naturally cite *i* where *L* is the citation matrix. Bibliographic coupling follows the same principles. Bibliographic coupling is the process of connecting papers that quote the same sources. If both papers *i* and *j* cite paper *k*, then there may be a connection between them. B_{ij} indicates how many papers are cited in both papers *i* and *j* as presented in equation (7).

$$B_{ij} = \sum_{k=1}^{n} L_{ik} L_{jk} \quad (7)$$

Naturally, there are B_{ii} references in paper *i* is reference list. The square matrix *B* that represents the bibliographic coupling matrix may be produced using B_{ij}. In order to establish how closely two publications are connected, clustering uses bibliographic coupling, which is also symmetric.

3.5 Page Rank

1998 was a watershed moment for web link analysis methods. Both the PageRank and HITS algorithms were published in the same year. There is a significant link between PageRank and HITS because of query independence, spam-prevention capabilities, and Google's tremendous financial success. Since that historic year, PageRank has established itself as the primary link analysis approach. The Page Rank algorithm from Google is used to rank websites in search engine results (Kumar, et al., 2013). PageRank uses the democratic nature of the web's link structure to determine pageworth or quality. PageRank interprets a link from page *x* to page *y* as a vote for page *y* from page *x*. PageRank, on the other hand, takes into account more than simply the number of votes cast; it also takes into account the page that casts the vote. The following are the steps for computing PageRank using the Markov chain:

1. Each page is a state, *i* = 1, ..., *N*.
2. Create a hypothetical state called *Restart* page, and identify it as state 0.
3. The following are the transition probabilities between states.

It is worth noting that the transition probability$p_{j,i}$is the probability of entering state*i* provided that the current state is *j*. For each *j*, valid transition probabilities must fulfil *I* $p_{j,i}$= 1. The likelihood of transitioning from state *j*, *j* = 0, to state *i*, *i* = 0, is presented in equation (8).

$$p_{j,i} = \frac{d}{C(j)} \times I(j \ links \ to \ i) \quad (8)$$

Let πi the stationary probabilities (i.e., limiting probabilities) of state *i*. According to a Markov chain theorem, these probabilities meet the following set of linear equations (9)-(14):

$$\pi_i = \sum_{j=0}^{N} \pi_j p_{j,i} \qquad i = 0,1,\dots,N \quad (9)$$

$$\sum_{i=0}^{N} \pi_i = 1 \quad (10)$$

Substitute to the Markov chain (9):

$$\pi_o = \sum_{j=0}^{N} \pi_j p_{j,o} = \sum_{j=0}^{N} \pi_j (1-d) = (1-d) \sum_{j=0}^{N} \pi_j = 1-d \quad (11)$$

$$\pi_i = \pi_o p_{o,i} + \sum_{j=1}^{N} \pi_j p_{j,i} = (1-d).\frac{d}{N} + \sum_{j:i(linked \ to \ j} \pi_j \frac{d}{C(j)} \quad (12)$$

Multiple (12) equation by$\frac{N}{d}$

$$\frac{N}{d}\pi_i = (1-d) + \sum_{j:i \ linked \ to \ j} \left(\frac{N}{d}\pi_j\right) \frac{d}{C(j)} \quad (13)$$

Define the PageRank as $PR(i) = \frac{N}{d}\pi_i$, we get:

$$PR(i) = (1-d) + \sum_{j:i \ linked \ to \ j} PR(j) \frac{d}{C(j)} \quad (14)$$

3.6 Data Collection

Researchers may search and assess funds, parents, clinical trials, policy papers, and publications using the extensive database known as Dimensions. Over 1.2 billion citations are found in Dimensions, which contains over 106 million publicly accessible publications. Authors, authors' affiliation with the name of the research organization, authors' affiliation with the country of the research organization, the dimensions url, times cited, and cited references are just a few of the characteristics that can be found in the Dimensions database and used for scientometric research. On November 2, 2021, we identified publications in the Dimensions database using the following search method: optimization and machine learning. No language restrictions applied, and only complete pieces were accepted. To make sure that our search strategy was reliable, we carefully examined the publications that were found. Study findings that were published between 2015 and 2021 in domestic and international journals were used to compile the data for Dimensions. In order to create a single journal list, we integrated all seven files after retrieving 2500 entries for each year from 2015 to 2021. The aggregate journal list in the Dimensions database had 17,500 articles. The database information was all gathered and saved in Excel forms.

4. Result and Discussion

Here, we give a description of the experiments' methodology and report the findings. Data from study findings published in national and international publications from 2015 to 2021 are included in the Dimensions database. For the years 2015 through 2021, we downloaded 2500 items. These seven files were eventually combined to produce a single journal list. 17,500 items made up the whole journal list in the Dimensions database. We gathered and stored all of the data from the retrieved papers in Excel format. Table 1 displays each entry that was taken from the Dimensions database. The downloaded database contains 387,328 references and 17,500 articles. In this study, single authors have 589 publications, whereas multi-author works have 40,853 publications. Fig. 1 shows the average number of article citations per year from 2015 to 2021. There is a slight increase in cited papers between 2016 and 2017 and a later decline from 2017 to 2020. According to the cited paper, the year 2021 had a greater upward trend than all other years. Fig. 2 shows the top 20 authors' productivity this year in machine learning and optimization. The larger the circle, the more articles each author has published in each year. Wang Y tops the list with the highest number of articles between 2015 and 2017, followed by Zhang Y and Li Y. Fig. 3 shows a visualisation of the co-citation network in two groups of 20 of the most regularly cited papers. Each publication of the article is depicted in a circle and is designated by the author's name and year. The colour of a publication indicates which cluster it belongs to, with red and blue representing Clusters 1 and 2, respectively. In cluster 1, the three most co-cited documents are Breiman I (2001), Cortes C (1996), and Chang C (2011), while in cluster 2, the three most co-cited documents belong to Lecum Y (2015), He K (2016), and Krizhevsky (2017), respectively. The most relevant keywords in optimization and machine learning are shown in Figure 4. Machine learning has the highest keyword density of all other methods. Optimization keywords came in 8th in the words observed from the database, followed by classification and networks. Table 2 is the collaborative network of the top 50 countries in optimization and machine learning between 2015 and 2021. The first, second, third, and fourth columns in the table are the country node, betweeness centrality, closeness centrality, and pagerank, respectively. In cluster 1, the United States of America, China, and Australia take the lead in the collaborative network, while in cluster

2, the United Kingdom, Germany, and Italy rank highly in their collaborative network. India, Iran, and Turkey ranked highly in the collaborative network of Cluster 3. Fig. 5 is the plot of cluster means against betweeness. The graph above depicts how cluster means change as the number of countries considered increases. The result shows that the means differ among the clusters, with cluster 3 presenting the lowest value and cluster 1 the highest. Fig. 6 is the plot of cluster means against closeness. The above graph shows how cluster means change between closeness and centrality, as well as the number of countries taken into account. The result shows that the means differ among closeness, with cluster 3 presenting the lowest value and cluster 1 the highest. Fig. 7 is the plot of cluster means against pagerank. The graph above depicts how cluster means change depending on pagerank and the number of countries considered. The results show that the means vary by pagerank, with cluster 3 having the lowest value and cluster 1 having the highest. Table 3 shows a two-way ANOVA to determine whether or not there is a significant difference in closeness and pagerank. The result reveals that the p-value is lower than the usual threshold of 0.05. This means that there is a statistical difference in betweenness centrality between closeness and pagerank.

Table 1 Descriptions of the dataset

Description	**Results**
Sources (Journals, Books, etc)	2065
Article	17500
References	387,328
Authors	41442
Author Appearances	83102
Authors of single-authored documents	589
Authors of multi-authored documents	40853

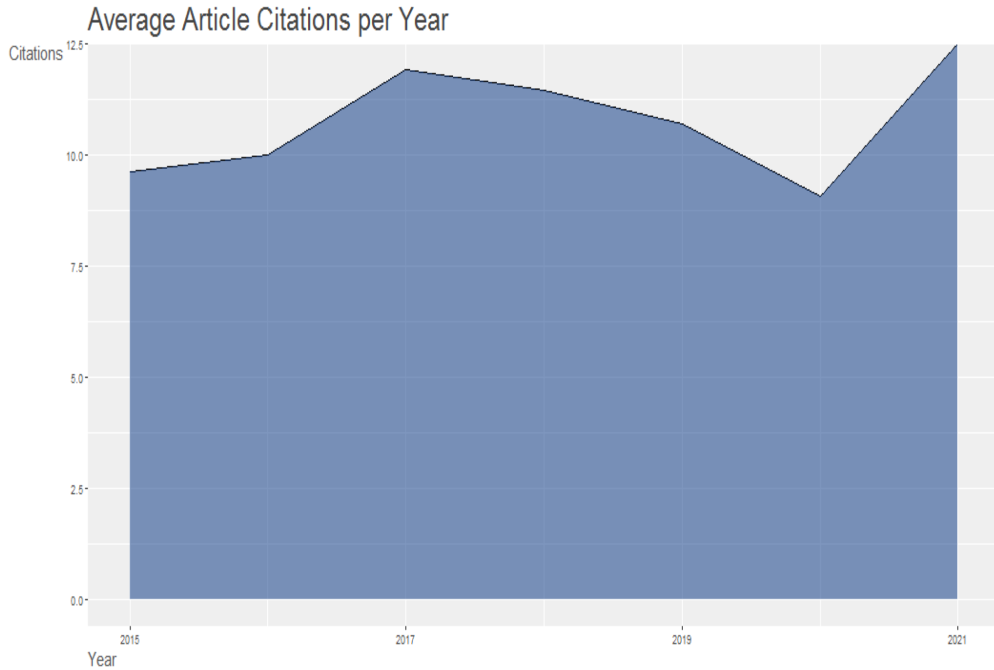

Figure 1 Average Article Citations per year

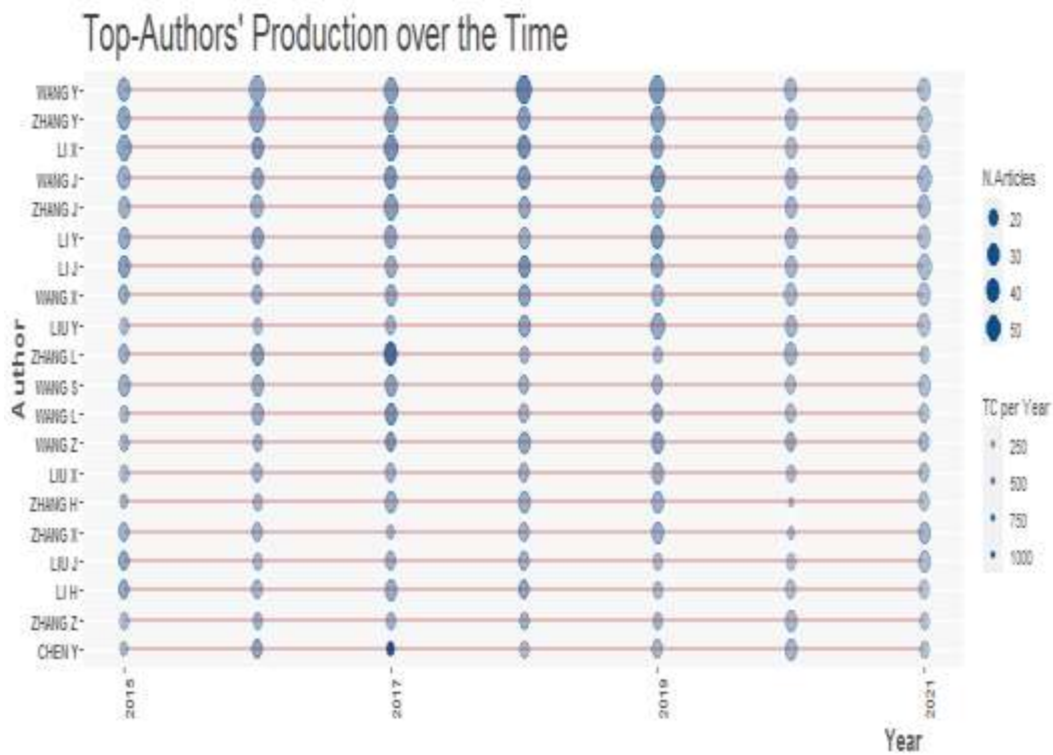

Figure 2 Top 20 Author Production between 2015-2021

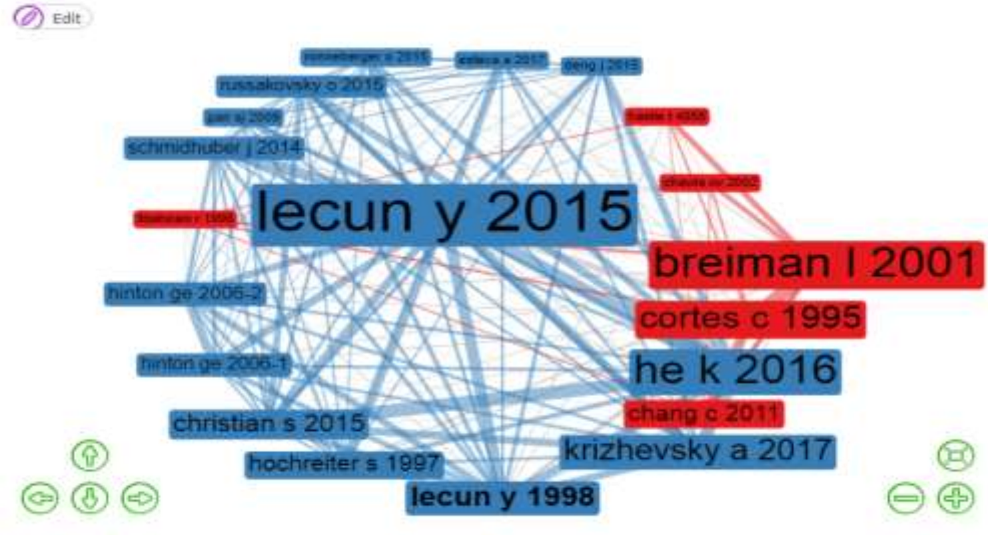

Figure 3 Cocitation Network of Articles

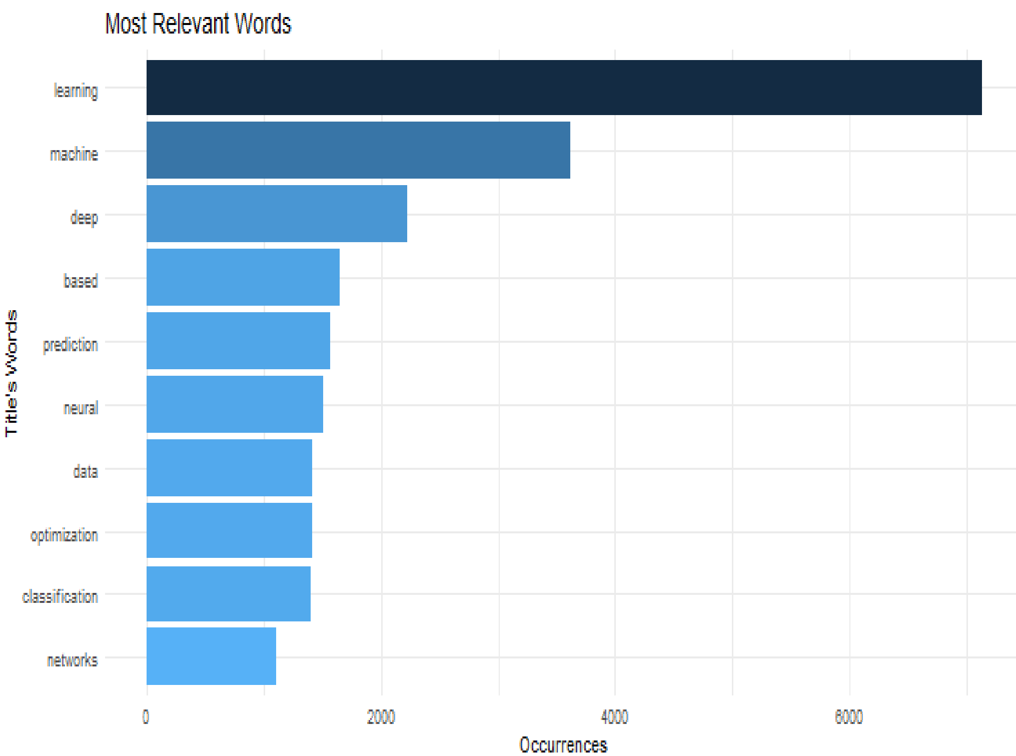

Figure 4 Most Relevant words between 2015-2021

Table 2 Collaborative Network of Country in Optimization and Machine Learning

Node	Cluster	Betweenness	Closeness	PageRank
United states	1	250.2003	0.020408	0.144876
China	1	70.53502	0.019231	0.117941
Australia	1	21.578	0.017857	0.046038
Canada	1	16.7128	0.017544	0.037965
Japan	1	3.211086	0.015152	0.020817
South Korea	1	3.984606	0.015152	0.026011
Singapore	1	1.562188	0.014493	0.025516
Taiwan	1	0.691806	0.012987	0.012375
Israel	1	0	0.010989	0.005206
New Zealand	1	0.085281	0.012195	0.006073
Thailand	1	0.024719	0.011494	0.0053
United Kingdom	2	106.9198	0.02	0.073895
Germany	2	35.02195	0.018182	0.047939
Italy	2	8.012262	0.016949	0.026712
France	2	6.062903	0.016129	0.024129
Spain	2	10.20898	0.016393	0.021145
Switzerland	2	1.532336	0.014085	0.022295
Netherlands	2	5.097322	0.015625	0.020226
Brazil	2	1.56816	0.014085	0.011714
Belgium	2	0.348272	0.013699	0.014716
Sweden	2	4.271693	0.015873	0.016582
Finland	2	1.057398	0.013514	0.010898
Greece	2	0.273154	0.012987	0.008495
Portugal	2	0.637995	0.013514	0.00902
Austria	2	0.252741	0.012987	0.010435
Denmark	2	0.933247	0.014085	0.01136
Norway	2	0.615724	0.013889	0.009615
Czechia	2	0.040009	0.012346	0.006177
Hungary	2	0.078905	0.011765	0.006015
Slovenia	2	0.010697	0.011628	0.004854
Colombia	2	0.026517	0.011364	0.004844
Ireland	2	0.018684	0.012048	0.005679
India	3	11.62074	0.016949	0.021524

Iran	3	4.080418	0.014286	0.017605
Turkey	3	0.544825	0.012821	0.00829

Table 2 (Continued)

Saudi Arabia	3	6.933477	0.014925	0.020351
Poland	3	2.050703	0.014706	0.012725
Malaysia	3	9.909801	0.014286	0.017764
Pakistan	3	0.755714	0.013333	0.010854
Egypt	3	1.470278	0.013333	0.00953
Russia	3	0.578326	0.013699	0.009269
Vietnam	3	2.543058	0.013889	0.012458
Mexico	3	0.134492	0.011905	0.00544
United Arab Emirates	3	0.317153	0.0125	0.007052
Romania	3	0.006393	0.011364	0.004673
South Africa	3	0.052283	0.011765	0.005175
Qatar	3	0.153287	0.012048	0.006798
Iraq	3	0.1944	0.012048	0.005898
Bangladesh	3	0	0.011236	0.004581
Nigeria	3	0.080124	0.011364	0.00515

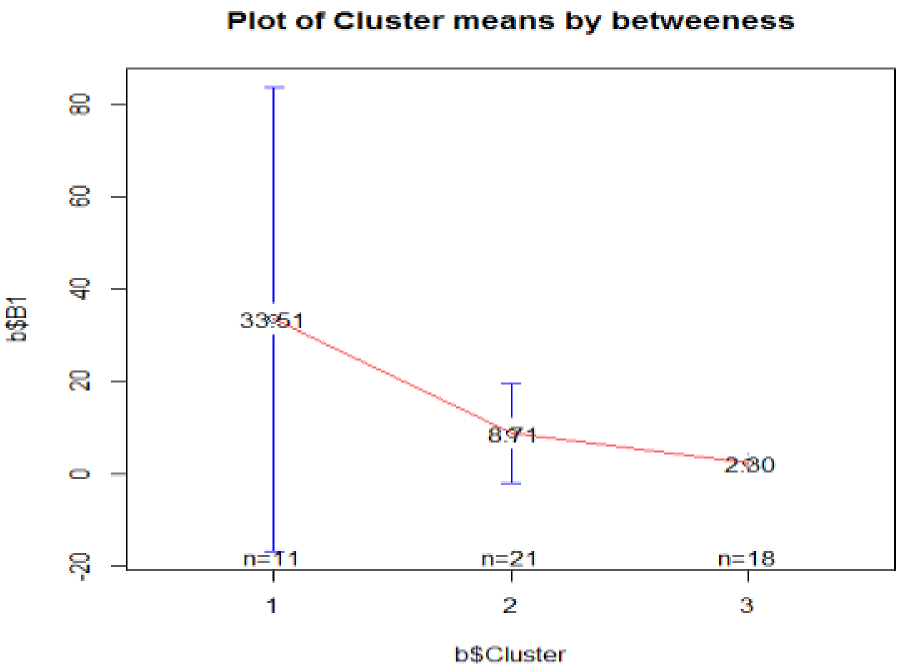

Figure 5 Plot of Cluster means by betweeness

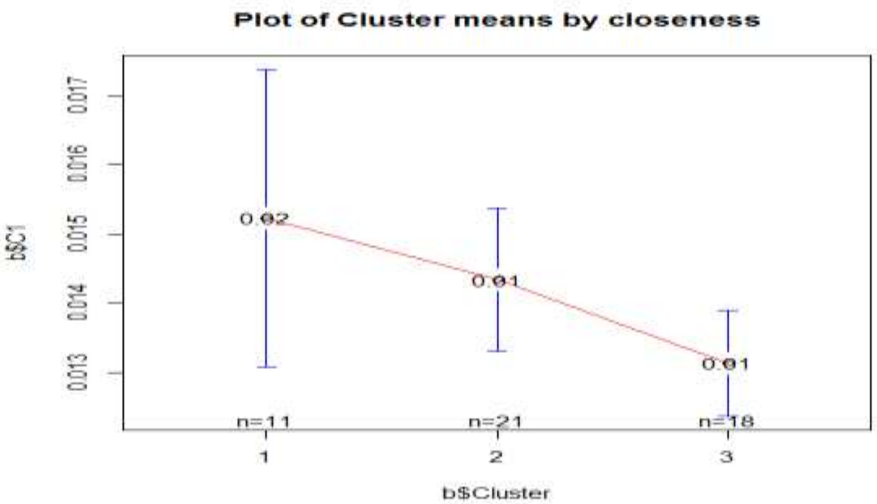

Figure 6 Plot of Cluster means by closeness

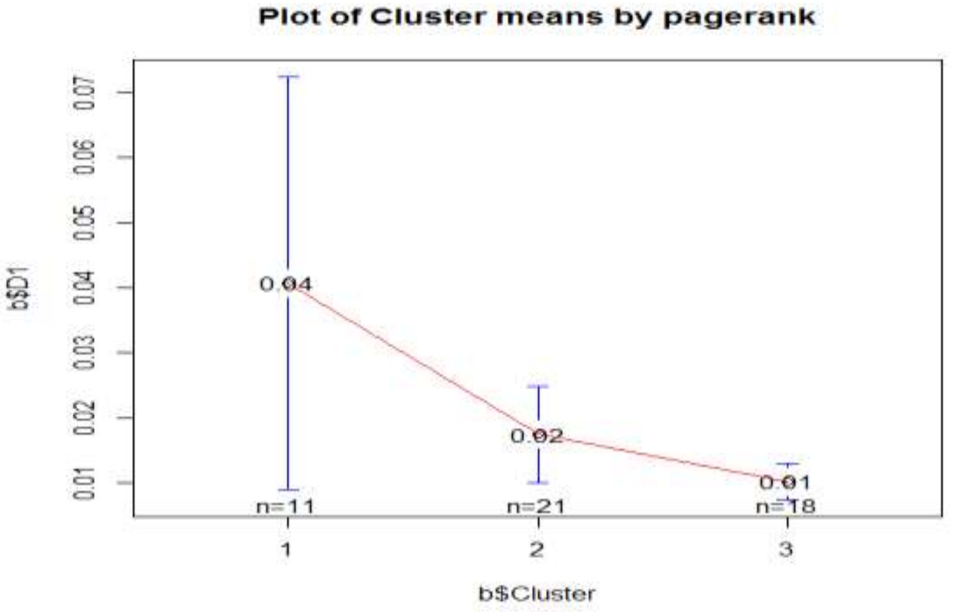

Figure 7 Plot of Cluster means by pagerank

Table 3 Two way ANOVA

Sources of Value	Degrees of freedom	Sum of Squares	Mean Square	F-Value	Pr(>F)
Between Closeness	1	31841	31841	118.3	2×10^{-14}
Between Pagerank	1	30048	30048	111.6	5.29×10^{-14}
Residual	47	12655	269		
Total	49	74544			

5. Conclusion

This report gives a complete summary of the most productive authors and important nations in optimization and machine learning between 2015 and 2021. The key benefit of this technique is that it discovers the most productive writers and prominent nations in optimization and machine learning by accounting for change over time. The reader will be able to identify where cutting-edge research is being conducted, as well as which countries are leading each of the main publications in optimization and machine learning. From this vantage point, it is fascinating to follow the history of authors and nations across time. Between 2015 and 2021, the United States and China dominated academic research, and this dominance is shifting in favour of nations in North America and Asia. The Dimensions database was used to collect data for this investigation. This work may lead to the following conclusions: To begin, the number of cited articles climbed considerably between 2016 and 2017, then declined from 2017 to 2020. In 2021, the number of cited publications climbed more than in any previous year. Second, Wang Y. and Zhang Y. are the most productive authors. The three most co-cited documents in cluster 1 are Breiman I, 2001; Cortes C, 1995; and Chang C, 2011; whereas the three most co-cited publications in cluster 2 are Lecum Y, 2015; He K, 2016; and Krizhevsky, 2017. Finally, our study demonstrates that, in a collaborative network of nations, there is a statistical difference in centrality between proximity and pagerank. Future trends suggest that colleges in North America and Asia may continue to expand their research into optimization and machine learning. A future study is anticipated to apply additional methods, notably graphical output from the VOS viewer application, for examining the top countries in terms of bibliographic content published through optimization and machine learning.

References

Karpathy A, Toderici G, Shetty S, Leung T, Sukthankar R, Fei-Fei L (2014). Large-scale video classification with convolutional neural networks. InProceedings of the IEEE conference on Computer Vision and Pattern Recognition, pp. 1725-1732.

Alfa AA, Misra S, Attah BI, Ahmed KB, Oluranti J, Ahuja R, Damasevicius R. (2022). Nigeria Human Population Management Using Genetic Algorithm Double Optimized Fuzzy Analytics Engine Approach. InEmerging Technologies for Computing, Communication and Smart Cities, pp. 203-215. Springer, Singapore.

Talavera A, Luna A. (2020). Machine learning: A contribution to operational research. IEEE Revista Iberoamericana de Tecnologias del Aprendizaje. 15(2):70-5.

Asadi S., Hussin, ARC, Dahlan, H M (2017). Organizational research in the field of Green IT: A systematic literature review from 2007 to 2016. Telematics and Informatics, 34, pp. 1191–1249.

Avkiran NK, Alpert K. (2015). The influence of co-authorship on article impact in OR/MS/OM and Theexchange of knowledge with finance in the twenty-first century. Annals of Operations

Research, 235(1),pp. 51–73.

Baardman L, Levin I, Perakis G, Singhvi D., (2017). Leveraging comparables for new product sales forecasting. *Working paper*.

Crawford B, Soto R, Johnson F, Misra S, Paredes F, Olguín E. (2015). Software project scheduling using the hyper-cube ant colony optimization algorithm. Tehnički vjesnik. 2015 Oct 22;22(5):1171-8.

Bernstein F, Modaresi S, Sauré D. (2019). A dynamic clustering approach to data-driven assortment personalization. Management Science 65(5):2095–2115.

Bengio Y, Lodi A, Prouvost A. (2018). Machine Learning for Combinatorial Optimization: A Methodological Tour d'Horizon. [online]. arxiv preprint. Available at: [Accessed 22 November 2022].

Bernstein F, Modaresi S, Sauré D., (2019). A dynamic clustering approach to data-driven assortment personalization. Management Science 65(5):2095–2115.

Bezdek JC. (1973). Fuzzy mathematics in pattern classification. Ph.D. thesis, Cornell University, Ithaca, NY.

Biscaro C, Giupponi C. (2014). Co-Authorship and Bibliographic Coupling Network Effects on Citations. PLos ONE 9 (6): e99502. doi:10.1371/journal.pone.

Kulis B, Basu S, Dhillon I, Mooney R. (2005 Aug 7). Semi-supervised graph clustering: a kernel approach. InProceedings of the 22nd international conference on machine learning, pp. 457-464).

Ding C, He X, Zha H, Simon HD (2002). Adaptive dimension reduction for clustering high dimensional data. In2002 IEEE International Conference on Data Mining, 2002. Proceedings. 2002 Dec 9 (pp. 147-154). IEEE.

Chen H, Engkvist O, Wang Y, Olivecrona M, Blaschke, (2018). The rise of deep learning in drug discovery. Drug Discov. 23, 1241–1250. [CrossRef] [PubMed]

Crawford B, Soto R, Palma W, Aballay F, Lemus-Romani J, Misra, S, Rubio J M. (2020). A Teaching-Learning-Based Optimization Algorithm for the Weighted Set-Covering Problem. Tehnički vjesnik, 27(5), 1678-1684. https://hrcak.srce.hr/file/355779

Cosi´c K, Popovi´c S, Šarlija M, Kesedži´c I, Jovanovic T. (*2020*). Artificial intelligence in prediction of mental health disorders induced ´ by the covid-19 pandemic among health care workers. Croat. Med. J., 61, 279. [CrossRef]

Cui R, Gallino S, Moreno A, Zhang DJ., (2018). The operational value of social media information. Production and Operations Management 27(10):1749–1769.

Oyewola D, Hakimi D, Adeboye K, Shehu MD. (2016). Using five machine learning for breast cancer biopsy predictions based on mammographic diagnosis. International Journal of Engineering Technologies IJET.

2(4):142-5.
Dada EG, Christopher N, Yetunde DC. (2017). Performance comparison of machine learning techniques for breast cancer detection. Nova. 2017;6(1):1-8.
Oyewola DO, Dada EG, Olaoluwa OE, Al-Mustapha KA. (2019). Predicting Nigerian stock returns using technical analysis and machine learning. European Journal of Electrical Engineering and Computer Science. 28;3(2).
Ciregan D, Meier U, Schmidhuber J. (2012). Multi-column deep neural networks for image classification. In2012 IEEE conference on computer vision and pattern recognition. pp. 3642-3649. IEEE.
Derviş H. (2019). Bibliometric Analysis using Bibliometrix an R Package .Journal of Scientometric Res. 8(3):156-160.
Cheung E. (2018). Optimization Methods for Semi-Supervised Learning. Waterloo, *ON, Canada: Univ.*
Eiselt H.A, Sandblom CL. (2010). Operations Research. Berlin, Heidelberg: Springer Berlin Heidelberg.
Fraley C, Raftery AE. (2002). Model-based clustering, discriminant analysis, and density estimation. Journal of the American statistical Association, pp. 611-631.
Murtagh F. (1983). A survey of recent advances in hierarchical clustering algorithms. The computer journal. vol. 26, no. 4, pp. 354–359.
Fraley C, Raftery AE. (2002). Model-based clustering, discriminant analysis, and density estimation. Journal of the American statistical Association, pp. 611-631.
Fuchs C. (2017). Sustainability and community networks. Telematics and Informatics, 34, pp. 628–639.
Gallacher G, Hossain I. (2020). Remotework and employment dynamics under COVID19*:* Evidence from Canada. Can. Public Policy, 46, S44–S54. [CrossRef]
Bastani H, Zhang DJ, Zhang H. (2022). Applied machine learning in operations management. InInnovative Technology at the Interface of Finance and Operations. pp. 189-222. Springer, Cham. *https://ssrn.com/abstract=3736466*.
Han P, Shi J, Li X, Wang D, Shen S, Su X. (2014). International collaboration in LIS: global trends and networks at the country and institution level. Scientometrics. 98(1):53-72.
Hillier FS, Lieberman GJ. (2010). Introduction to operations research. 9th ed.Boston: McGraw-Hill.
Hinton GE. (2010). A practical guide to training restricted Boltzmann machines. InNeural networks: Tricks of the trade. pp. 599-619. Springer, Berlin, Heidelberg.
Hinton G, Sejnowski TJ (1999). editors. Unsupervised learning: foundations of neural computation. MIT press.
Rodríguez-Rodríguez I, Rodríguez JV, Shirvanizadeh N, Ortiz A, Pardo-Quiles DJ. (2021). Applications of artificial intelligence, machine learning, big data and the internet of

things to the covid-19 pandemic: A scientometric review using text mining. International Journal of Environmental Research and Public Health. 18(16):8578..

Hartigan JA, Wong MA. (1979). Algorithm AS 136: A k-means clustering algorithm, J. Roy. Stat. Soc. C (Appl. Stat.), vol. 28, no. 1, pp. 100–108.

Dornemann J, Rückert N, Fischer K, Taraz A. (2020). Artificial intelligence and operations research in maritime logistics. InData Science in Maritime and City Logistics: Data-driven Solutions for Logistics and Sustainability. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol. 30, pp. 337-381. Berlin: epubli GmbH.

Yang J, Yu K, Gong Y, Huang T. (2009). Linear spatial pyramid matching using sparse coding for image classification. In 2009 IEEE Conference on computer vision and pattern recognition 2009 Jun 20, pp. 1794-1801. IEEE.

Kandiller L. (2007). Principles Of Mathematics In Operations Research. New York, Turkey: Springer.

Kaufmann L. (1987). Clustering by means of medoids. In Proc. Statistical Data Analysis Based on the L1 Norm Conference, Neuchatel, pp. 405-416.

Kumar R, Goh A, Ashutosh KS. (2013). Application of Markov Chain in the PageRank Algorithm. Pertanika J. Sci. & Technol. 21 (1): 541 – 554.

Leonardi PM. (2020). COVID-19 and the new technologies of organizing: Digital exhaust, digital footprints, and artificial intelligence in the wake of remote work. J. Manag. Stud. 12648, Epub ahead of print. [CrossRef]

Maharani W, Gozali AA. (2014). Degree centrality and eigenvector centrality in twitter. In2014 8th international conference on telecommunication systems services and applications (TSSA) 2014 Oct 23 (pp. 1-5). IEEE..

Kraus M, Feuerriegel S, Oztekin A. Deep learning in business analytics and operations research: Models, applications and managerial implications. European Journal of Operational Research. 2020 Mar 16;281(3):628-41.

Chui M, Manyika J, Miremadi M, Henke N, Chung R, Nel P, Malhotra S. (2018). Notes from the AI frontier: Insights from hundreds of use cases. McKinsey Global Institute. 2018 Apr 8:28.

Meng Q, Wang S, Andersson H, Thun K. (2014). Containership Routing and Scheduling in Liner Shipping: Overview and Future Research Directions. Transportation Science, 48(2), pp. 265–280.

Chapelle O, Sindhwani V, Keerthi S. S. (2008). Optimization techniques for semi-supervised support vector machines, J. Mach. Learn. Res., vol. 9, pp. 203–233.

Ogundokun RO, Misra S, Douglas M, Damaševičius R, Maskeliūnas R. (2022). Medical Internet-of-Things

Based Breast Cancer Diagnosis Using Hyperparameter-Optimized Neural Networks. Future Internet. 14(5):153.

Ogundokun RO, Maskeliunas R, Misra S, Damaševičius R. (2022). Improved CNN Based on Batch Normalization and Adam Optimizer. InInternational Conference on Computational Science and Its Applications. pp. 593-604. Springer, Cham.

Okewu E, Misra S, Maskeliūnas R, Damaševičius R, Fernandez-Sanz L. (2017). Optimizing Green Computing Awareness for Environmental Sustainability and Economic Security as a Stochastic Optimization Problem. Sustainability, 9(10), 1857.

Saclay P. (2018). Operations Research & Machine Learning. Brief summary of main topics emerged during the parallel session of the 1st workshop of the Working Group on Practice of OR, collected by Matteo Pozzi.

Pan SJ, Yang Q. (2009). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering 22(10):1345–1359.

Chen P, Jiao L, Liu F, Zhao J, Zhao Z, Liu S. (2017). Semi-supervised double sparse graphs based discriminant analysis for dimensionality reduction. Pattern Recognition.. 61:361-78.

Nerurkar P, Shirke A, Chandane M, Bhirud S. Empirical analysis of data clustering algorithms. Procedia Computer Science. 2018 Jan 1;125:770-9.

Rana N, Abd Latiff MS, Abdulhamid SI, Misra S. (2021). A hybrid whale optimization algorithm with differential evolution optimization for multi-objective virtual machine scheduling in cloud computing. Engineering Optimization. 2021 Sep 10:1-8.

Rodríguez-Rodríguez I, Zamora-Izquierdo MÁ, Rodríguez JV. (2018). Towards an ICT-based platform for type 1 diabetes mellitus management. Appl. Sci., 8, 511.

Rusmevichientong P, Shen ZJM, Shmoys DB. (2010). Dynamic assortment optimization with a multinomial logit choice model and capacity constraint. Operations Research 58(6):1666–1680.

Sun S, Cao Z, Zhu H, Zhao J. (2019). A survey of optimization methods from a machine learning perspective. IEEE transactions on cybernetics. 18;50(8):3668-81.

Sun S, Cao Z, Zhu H, Zhao J. A survey of optimization methods from a machine learning perspective. IEEE transactions on cybernetics. 2019 Nov 18;50(8):3668-81.

Song M, Ding Y. (2014). Topic modeling: Measuring scholarly impact using a topical lens. In Measuring Scholarly Impact; Springer: Cham, Switzerland; pp. 235–257.

Stuart J. (2010). Artificial Intelligence A Modern Approach Third Edition.

Talluri K, Van Ryzin G. (2004). Revenue management under a general discrete choice model of consumer behaviour. Management Science 50(1):15–33.

Ting DSW, Carin L, Dzau V, Wong TY. (2020). Digital technology and COVID-19. Nat. Med. 26, 459–461.

Van Eck N, Waltman L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. scientometrics. 84(2):523-38.

Van Eck N, Waltman L. (2014). Visualizing bibliometric networks. In Measuring Scholarly Impact; Springer: Cham, Switzerland; pp. 285–320.

van Eck N, Waltman L, Noyons E, Buter R. (2010). Automatic term identification for bibliometric mapping. Scientometrics. 2010 Mar 1;82(3):581-96.

Wenpeng Y, Schütze H. Multichannel variable-size convolution for sentence classification [C]. InProc of the 19th Conf on Computational Natural Language Learning. Stroudsburg, PA: ACL 2015 (pp. 204-214).

Yan E, Ding Y. (2012). Scholarly network similarities: How bibliographic coupling networks, citation networks, cocitation networks, topical networks, coauthorship networks, and coword networks relate to each other. Journal of the American Society for Information Science and Technology. 63(7):1313-26.

Yan E, Ding Y, Jacob EK. (2012). Overlaying communities and topics: An analysis on publication networks. Scientometrics. 90(2):499-513.

Bazi Y, Melgani F. (2009). Gaussian process approach to remote sensing image classification. IEEE transactions on geoscience and remote sensing. 48(1):186-97.

Li YF, Tsang IW, Kwok JT, Zhou ZH. Convex and scalable weakly labeled SVMs. Journal of Machine Learning Research. 2013 Jul 1;14(7).

Kim Y. (2014). Convolutional Neural Networks for Sentence Classification. EMNLP 2014–2014 Conf Empir Methods Nat Lang Process Proc Conf [Internet]. 2014 Aug 25 [cited 2020 Feb 19]; 1746–51.

Zhang B, Hsu M, Dayal U. (1999). K-harmonic means-a data clustering algorithm. Hewlett-Packard Labs Technical Report HPL-1999-124.

Zhou ZH, Li M. (2005). Semi-supervised regression with co-training. InIJCAI Vol. 5, pp. 908-913.

Dada EG, Oyewola DO, Joseph SB, Dauda AB. (2021). Ensemble Machine Learning Model for Software Defect Prediction. Advances in Machine Learning & Artificial Intelligence, 2 (1), 11-21.

Oyewola DO, Dada EG. (2022). Machine Learning Methods for Predicting the Popularity of Movies. Journal of Artificial Intelligence and Systems, pp. 65-82, DOI: 10.33969/AIS.2022040105

Dada EG, Oyewola DO, Joseph SB. (2022). Deep Convolutional Neural Network Model for Detection of Sickle Cell Anemia in Peripheral Blood Images. Communication in Physical Sciences. 2022 Mar 8;8(1).

Misra S. (2021). A step by step guide for choosing project topics and writing research papers in ICT related disciplines. InInternational conference on information and communication technology and applications 2021 (pp. 727-744). Springer, Cham.