INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT
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ISSN: 2226-6348

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To Link this Article: http://dx.doi.org/10.6007/IJARPED/v12-i2/17189 DOI:10.6007/IJARPED/v12-i2/17189

Received: *08* March 2023***, Revised:*** *13* April 2023***, Accepted:*** *29* April 2023

Published Online: *17* May 2023

In-Text Citation: (Abidin et al., 2023)

To Cite this Article: Abidin, N. H. Z., Sarudin, E. S., Aziz, W. N. H. W. A., Khalid, I. K., & Yusof, Y. (2023). Bibliometric Analysis of Neural Network in improving Computational Fluid Dynamics Education. *International Journal of Academic Research in Progressive Education and Development*, *12*(2), 905–916.

Vol. 11(2) 2023, Pg. 905 - 916

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Bibliometric Analysis of Neural Network in improving Computational Fluid Dynamics Education

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Abstract

The integration of neural networks into computational fluid dynamics (CFD) has led to significant advancements in fluid dynamics simulations, enhancing accuracy and effectiveness. This convergence presents a promising avenue for studying fluid systems and has the potential to revolutionize our understanding of their complex behaviours. To foster collaboration and drive research in this field, a comprehensive bibliometric review was conducted, examining the intersection of fluid dynamics education and neural networks. From a pool of 999 articles gathered from the Google Scholar database, 779 articles published between 2018 and 2023 were selected using the Publishing or Perish (PoP) software. These articles were analysed and categorized using VOSviewer, revealing three distinct clusters representing the primary research topics in computational fluid dynamics and neural networks. The findings of this study provide valuable insights into the current state of research in this emerging field, offering a comprehensive overview of key themes and their relationships. These insights can guide researchers and practitioners in identifying gaps, exploring collaborations, and advancing interdisciplinary approaches. Moving forward, further exploration of the identified clusters and associated keywords can deepen understanding of specific research topics, while investigations into methodologies and techniques employed in the articles can contribute to the development of advanced computational tools and frameworks for fluid dynamics simulations. Collaborative efforts and interdisciplinary approaches hold great potential for advancing our knowledge of fluid systems and driving progress in this exciting field.

Keywords: Bibliometric Analysis, Author Keyword Co-occurrences, Fluid Dynamics, Neural Network, VOSviewer.

Introduction

Machine learning has been gaining a lot of attention in the field of fluid dynamics recently due to its potential to accelerate simulations and improve accuracy (Vinuesa & Brunton, 2022). In recent years, there have been numerous studies that have demonstrated the effectiveness of machine learning in enhancing the understanding of fluid dynamics among students.

Traditionally, fluid dynamics education has relied on textbooks, lectures, and experiments. However, with the recent advancements in machine learning, there has been a shift towards incorporating this technology into the curriculum. End-to-end deep learning has been used to improve approximations inside computational fluid dynamics for modeling two-dimensional turbulent flows, resulting in computational speedups of up to 80-fold while maintaining accuracy comparable to traditional solvers (Kochkov et. al., 2021).
There are several areas where machine learning can be applied to improve fluid dynamics education. One example is the development of interactive simulations that allow students to manipulate parameters and observe how they affect fluid behaviour (Brunton et. al., 2020). Machine learning can also be used to develop personalized learning platforms that can adapt to individual student's needs and learning styles (Brunton, 2021). Additionally, machine learning can help bridge the gap between theory and experiments by developing predictive models that can accurately simulate real-world fluid dynamics problems.
In summary, machine learning has the potential to revolutionize fluid dynamics education by providing new and innovative ways to teach and learn in this field. Incorporating machine learning into the curriculum can lead to a better understanding of fluid dynamics, and prepare students for the growing demand for machine learning skills in various industries. In this paper, bibliometric analysis is used to reveal the increasing impact and dissemination of research in the intersection of fluid dynamics education with machine learning.
Bibliometric analysis is a popular method of analysing large volumes of scientific data, and it can be applied to various fields of research. In the case of fluid dynamics, bibliometric analysis can provide valuable insights into publishing trends, research topics, and collaborations. However, it is essential to define the aims and scope of the bibliometric study before selecting analysis techniques and gathering data (Donthu et. al., 2021).
Bibliometric analysis can unpack the evolutionary nuances of a specific field, providing insights into the most popular subjects covered, multidisciplinary articles, and the countries that contribute to the analysis. A keyword analysis is one way to identify popular subjects, and multidisciplinary articles tend to have the highest impact (Ellegaard & Wallin, 2015).
As Donthu et. al (2021) elucidates, this study applies the bibliometric analysis technique, utilizing tools such as VOSviewer and Publish or Perish (PoP) to create bibliometric networks and extract citation and publication data from sources like Google Scholar, Scopus, and Web of Science. Consequently, this research adheres to Sudrajat et. al (2022) recommended steps to conduct bibliometric analysis in the domain of neural network. The selected articles from the Google Scholar database were obtained via the PoP software, sorted into clusters, and presented using VOSviewer.

Data and Methodology

The primary method of analysis used in this study will be bibliometric analysis. Information pertaining to the selected keyword was gathered from the Google Scholar (GS) database as of March 8th, 2023. Ahmar et al (2018) claim that GS is a useful tool for researchers, giving them access to scientific information in a variety of media, such as books, journal articles, conference papers, patents, and other publications. As one of the largest indexers of web papers worldwide, its indexation can aid researchers in communicating their findings and enable other academics to reference their work. According to Ahmi et al (2019), the information that will be gathered will contain details like the publication type, year of publishing, author names, subjects, publisher's names, countries, affiliations, source types, and languages. By typing the selected keywords into the PoP software, the data will be captured.

The bibliometric analysis of fluid dynamics education with machine learning will next be shown utilising VOSviewer's examination of the amassed data. VOSviewer is a bibliometric programme that can translate the data from earlier studies into knowledge maps, as mentioned by (Yang et al., 2019). VOSviewer, in contrast to other applications, can do clustering analysis and generate three different knowledge maps: Network Visualisation, Overlays Visualisation, and Density Visualisation (Van Eck & Waltman, 2023). These maps show clusters of pertinent nodes that are coloured according to their classification. The quantity of documents and citations can be represented by the size of each node, which corresponds to the weight of each item (Li et al., 2021). The research will adhere to the five stages of the methodology proposed by Hudha et al (2020), as shown in Figure 1.

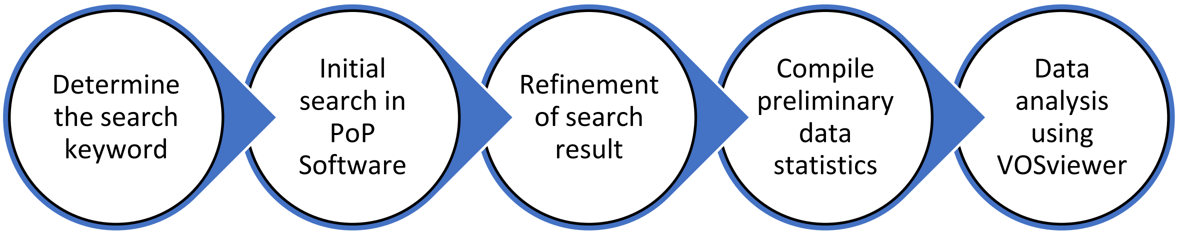

Fig. 1: Phases in Bibliometric Analysis

Defining Search Keywords
The term “Computational Fluid Dynamic and Neural network” was used in Mac 2023's literature search. Since Google Scholar is the largest database, the literature search for this study using the Publish or Perish (PoP) programme only focused on prior research in Google Scholar.

Initial Search Results
A literature search was done using Google Scholar on March 27, 2023, using the keyword "Computational Fluid Dynamic and Neural network". The search was conducted using the Publish or Perish (PoP) software. Google Scholar was chosen as the database for this study because of its thorough coverage of scholarly literature from a variety of areas, as mentioned by (Ahmar et. al., 2018). Using the PoP software guarantees that the search was methodical, thorough, and produced high-quality results. Overall, this method made it possible to locate a sizable number of articles pertaining to computational fluid dynamics and neural networks, offering a strong framework for performing a bibliometric investigation of this area.

Refinement Search Results

A total of 999 publications have been identified from the Google Scholar database's initial search. However, to ensure the quality and relevance of the selected articles, a manual screening process was conducted to exclude publications with incomplete information on the year of publication, publication name, and publisher name. Additionally, publications in books, book chapters, other languages, and patents were excluded, resulting in a final set of 779 publications for analysis. This screening process aligns with the guidelines for conducting bibliometric analysis, as noted by (Ahmi et. al., 2019). The selected publications were then saved in the RIS format, a standardized format for bibliographic data, for further analysis in Microsoft Excel and VOSviewer. This approach allows for a systematic and comprehensive analysis of the selected publications, enabling the identification of important patterns and trends in the research field of computational fluid dynamic and neural network.

Compiling Data Analysis

After the refining search step, the necessary data will be retrieved from PoP software and saved in RIS format. By exporting this RIS file into VOSviewer programme, the required data will be processed there. Author, title, publisher, publication name, year, and number of citations are all needed pieces of information.

Data Analysis

To identify the frequent keywords used in previous studies, the data collected from PoP software is analyzed using the VOSviewer software. As noted by Hudha et. al. (2020), VOSviewer software is a popular tool for processing large datasets and provides a range of visualizations, analyses, and investigations. Its efficiency in processing large datasets makes it an ideal choice for this study. Through the use of VOSviewer software, the analysis of the collected data will enable the identification of the most commonly used keywords in previous studies on the topic. This will allow for a better understanding of the key themes and trends in the literature and provide insights for future research.

Results and Discussions

Detection

In the initial search using the keyword "computational fluid dynamic & neural network" in the GS database via PoP software, 999 publications were found from 2018 to 2023, with 131506 citations, which averages to about 26301.20 citations per year. After carrying out the refinement search by searching the title words “computational fluid dynamic & neural network”, 220 publications were eliminated, resulting in 779 publications with 97663 citations, averaging 19532.60 citations per year. Table 1 presents the comparison of metric data from publications retrieved initially and after selection. According to (Hudha et. al., 2020). VOSviewer software is chosen for its ability to process large datasets efficiently and provide a variety of interesting visualizations, analyses, and investigations.

Table 1
Comparison Metrics

Metric Data	Initial Search	Refinement Search
Source	"Computational Fluid Dynamic & Neural network"	"Computational Fluid Dynamic & Neural network"
Publication year	2018-2023	2018-2023
Papers	999	779
Citations	131506	97663
Cites/year	26301.20	19532.60
Cites/paper	131.64	125.37
Author/paper	3.79	3.80
h_index	167	149
g_index	291	254
hI_norm	86	73
hI_annual	17.20	14.60
hA-index	82	70

This research study presented two main findings related to the topic of "computational fluid dynamic & neural network". The first finding focused on the number of citations for the selected publications. Through a refinement search stage, a total of 779 publications were selected and the top 10 publications with the highest number of citations were presented in Table 2. The results showed that all 10 selected papers had a minimum of 761 citations, with the highest cited paper being "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations" with 4894 citations, and the lowest cited paper being "DeepXDE: A deep learning library for solving differential equations" with 761 citations. This finding highlights the importance of the selected publications in the field and suggests that these papers have a significant influence in shaping research and policy discussions related to computational fluid and neural network.

Table 2
Top 10 cited articles

No	Publication Year	Authors	Title	Journal	No of Citation	Publisher
1	2019	M Raissi, P Perdikaris, GE Karniadakis	Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations	Journal of Computational physics	4894	Elsevier
2	2018	AG Baydin, BA Pearlmutter, AA Radul…	Automatic differentiation in machine learning: a survey	Journal of Machine Learning Research	2196	jmlr.org

3	2018	J Sirignano, K Spiliopoulos	DGM: A deep learning algorithm for solving partial differential equations	Journal of computational physics	1396	Elsevier
4	2020	SL Brunton, BR Noack…	Machine learning for fluid mechanics	Annual Review of Fluid Mechanics	1393	annualreviews.org
5	2021	GE Karniadakis, IG Kevrekidis, L Lu…	Physics-informed machine learning	Nature Reviews Physics	1311	nature.com
6	2018	X Lin, Y Rivenson, NT Yardimci, M Veli, Y Luo…	All-optical machine learning using diffractive deep neural networks	Science	1091	science.org
7	2019	K Duraisamy, G Iaccarino, H Xiao	Turbulence modeling in the age of data	Annual Review of Fluid Mechanics	858	annualreviews.org
8	2020	M Raissi, A Yazdani, GE Karniadakis	Hidden fluid mechanics: Learning velocity and pressure fields from flow visualizations	Science	814	science.org
9	2018	B Lusch, JN Kutz, SL Brunton	Deep learning for universal linear embeddings of nonlinear dynamics	Nature communications	779	nature.com
10	2021	L Lu, X Meng, Z Mao, GE Karniadakis	DeepXDE: A deep learning library for solving differential equations	SIAM review	761	Society for Industrial and Applied Mathematics (SIAM)

In addition to the citation analysis, this study also investigated the popular publishers that contributed the most publications on the topic of "computational fluid dynamic & neural network". From the total of 779 articles, the top 10 publishers were identified and presented in Figure 2. The results showed that Elsevier was the most popular publisher with 139 articles, followed by Wiley Online Library with 94 articles, and emerald.com with 77 articles. This finding provides insights into the publishing landscape and the key players in the field, which may help researchers and practitioners identify potential collaboration opportunities and stay updated with the latest research trends. Overall, these findings contribute to a deeper understanding of the research landscape related to computational fluid dynamics and neural networks.

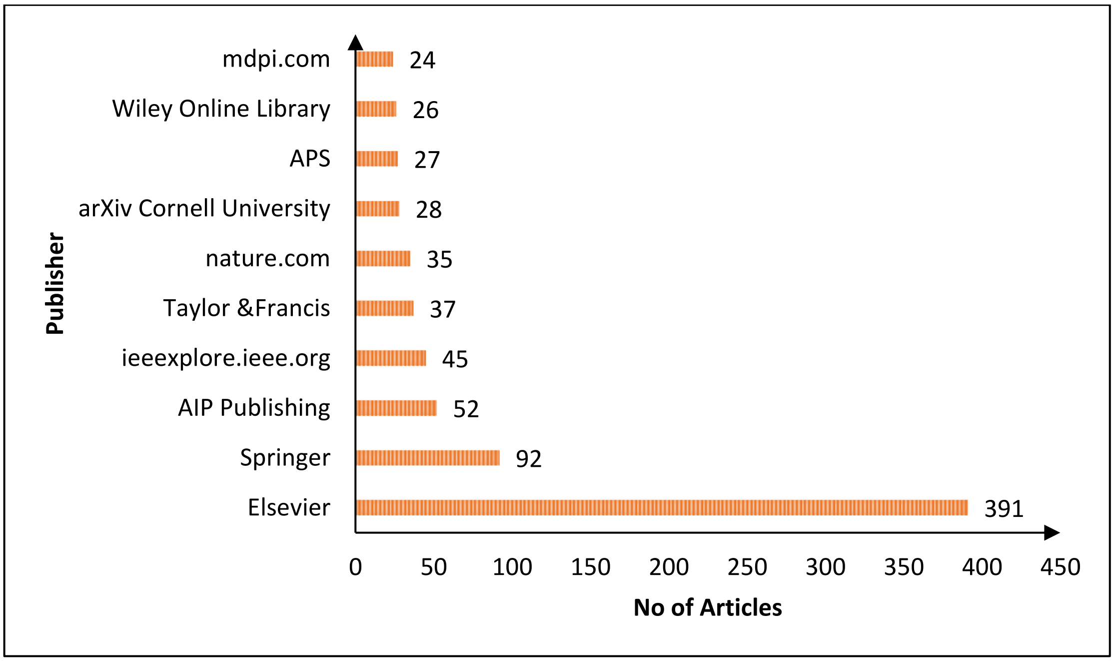

Fig. 2: Top 10 publishers who publish computational fluid dynamic and neural network topic

Table 3 displays the top 10 journals that have published articles related to the subject of computational fluid dynamics and neural networks, along with their respective number of articles published, number of citations, and average citations per article. It is shown that Journal of Computational Physics has the highest number of articles and highest average citations per article published on this topic with 45 articles and 282.18 citations.

Table 3
Top 10 journals that have relevant articles on Computational Fluid Dynamic and Neural Network topic

No	Journal Name	Total articles	Total Citations	Average Citation
1	Journal of Computational Physics	45	12698	282.18
2	Computer Methods in Applied Mechanics and Engineering	27	3937	145.81
3	Engineering Applications of Computational Fluid Mechanics	24	3008	125.33
4	Journal of Fluid Mechanics	21	2870	136.67
5	Neural Computing and Applications	15	1385	92.33
6	Nature communications	12	2318	193.17
7	Applied Thermal Engineering	12	815	67.92
8	Energy	12	768	64.00
9	Energy conversion and management	11	1249	113.55
10	AIAA journal	11	1305	118.64

Classification

The analysis of data retrieved from PoP software is conducted using VOSviewer software to identify frequently used keywords in previous studies. The number of frequently used keywords may vary depending on the requirements of data collection and analysis.

VOSviewer software is employed to visualize bibliometric maps, and it offers three visualizations for bibliometric mapping, including network visualization, overlay visualization, and density visualization.

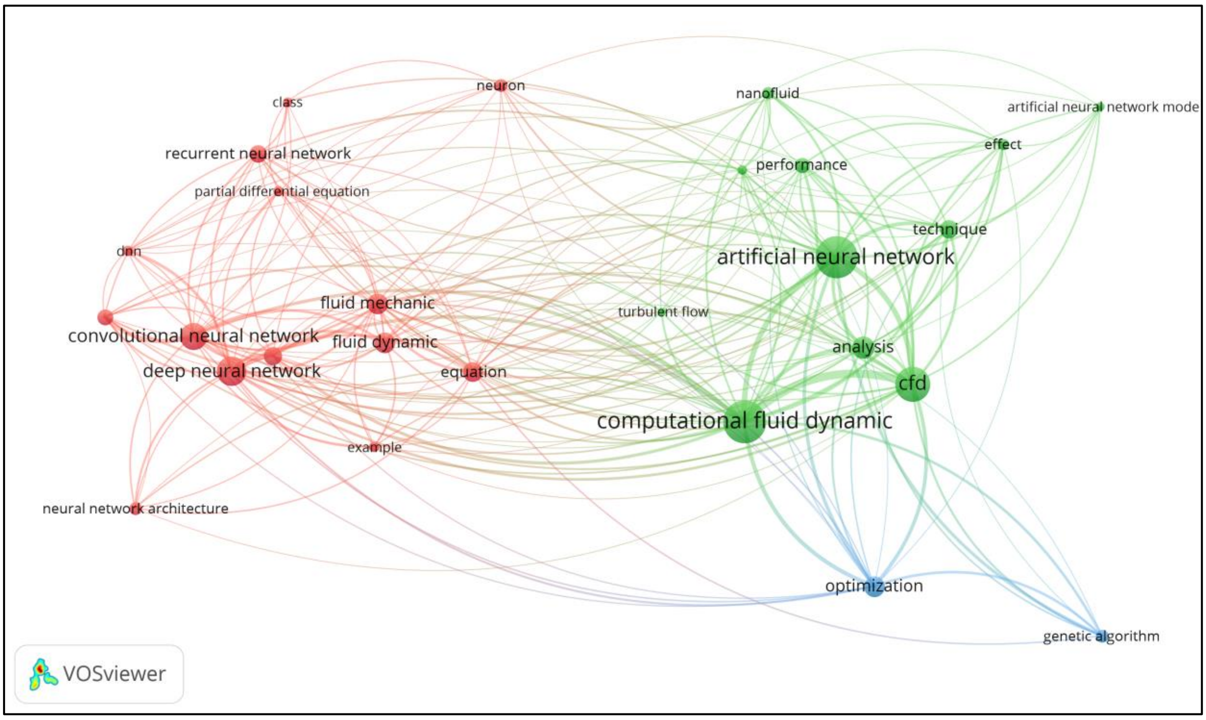

Fig. 3: Network visualization on GS database that related to computational fluid dynamic and neural network topic

The results in Fig.4 and Table 4 revealed the presence of three distinct groups of keywords and concepts within the context of clustering. The first cluster focuses on neural networks and fluid dynamics, the second cluster revolves around analysis and computational fluid dynamics, and the third cluster is centered around genetic algorithms and optimization techniques. The word 'computational fluid dynamic' was the most frequently encountered keyword with 191 occurrences and 428 links to other keywords. The use of VOSviewer software enabled a comprehensive analysis of the data from the PoP database, and the visualization of the results through the maps and clusters provides valuable insights into the distribution and relationships among the different keywords.

Table 4
Keyword representing each cluster determined by VOSviewer

No	Cluster	Elements
1	First cluster (Red)	class (14), cnn(34), convolutional neural network (87), deep learning (42), deep neural network (98), dnn (16), equation (49), example (16), fluid dynamic (55), fluid mechanic (53), neural network architecture (24), neuron (24), partial differential equation (17), recurrent neural network (41)
2	Second cluster (Green)	Analysis (60), artificial neural network (184), artificial neural network model (12), cfd (133), computational fluid dynamic (191), effect (19), heat transfer (14), nanofluid (21), performance (31), technique (43), turbulent flow (10)
3	Third cluster (Blue)	Genetic algorithm (23), optimization (55)

In Figure 4, the overlay visualization, each cluster represents an analysis of how the article's focus is distributed over time. This analysis helps identify the latest trends. Additionally, Figure 5 provides a visualization of keyword density used by the author. The intensity of the colour in the image indicates the density, whereas lighter colours indicate more frequent usage of the keyword. Overall, the use of VOSviewer software and the different types of maps created provide a clear and comprehensive representation of the analysed data, which can help researchers gain insights into the relationships and patterns within the data.

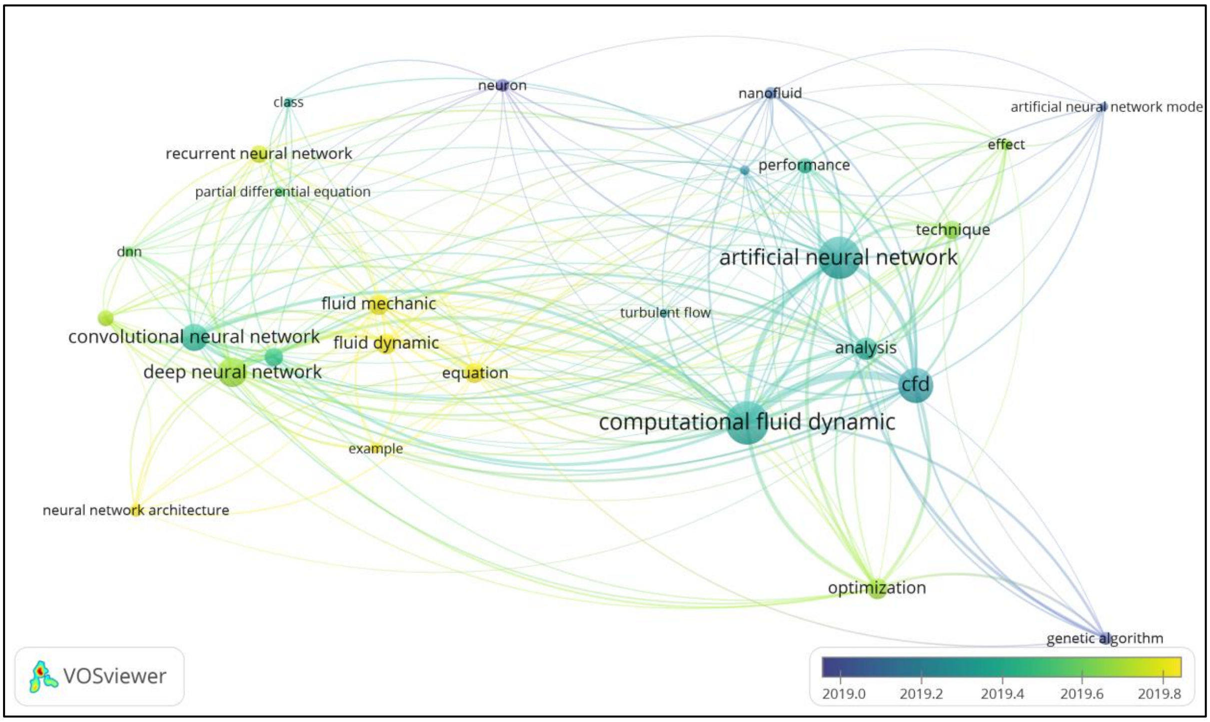

Fig. 4. Overlay visualization on GS database that related to computational fluid dynamic and neural network topic

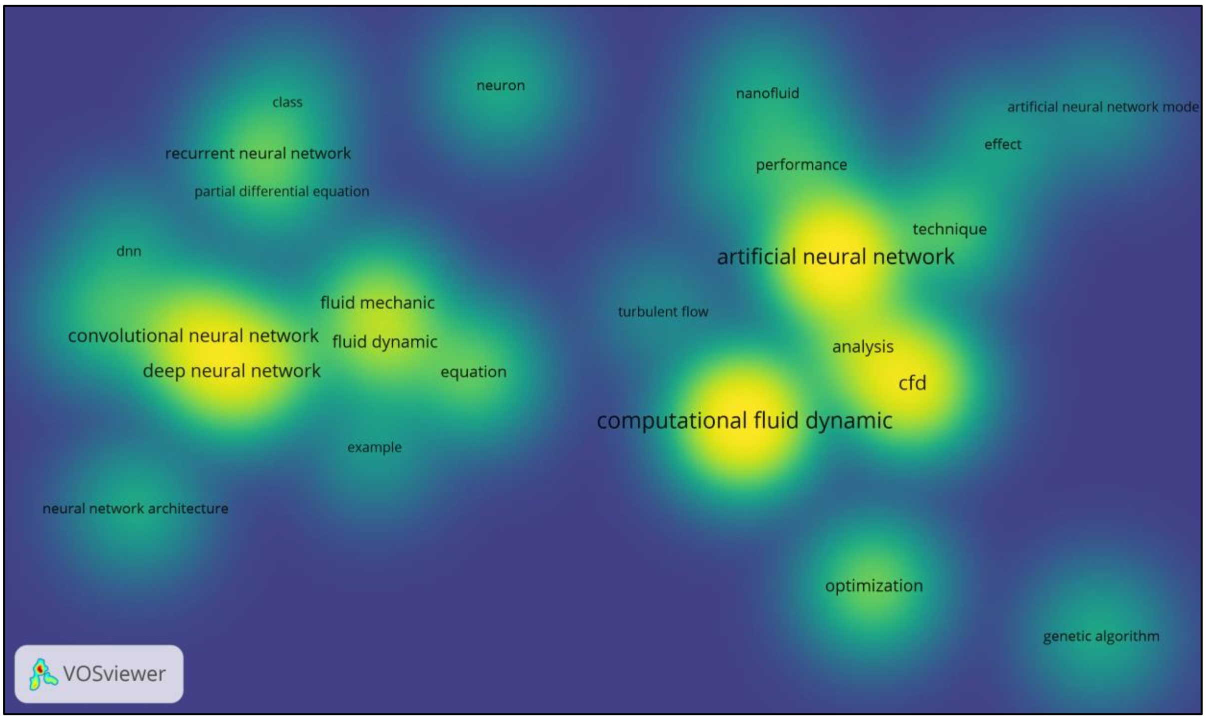

Fig. 5. Density visualization on GS database that related to computational fluid dynamic and neural network topic

Conclusions

This study utilizes a bibliometric approach to analyse the research output in the field of neural networks. The study employs PoP and VOSviewer software to conduct the analysis. Specifically, the PoP software is used to obtain 779 related journal articles from Google Scholar using the keyword "Computational Fluid Dynamic & Neural Network" These articles are then sorted according to various criteria, such as author, year of publication, publisher name, journal name, and citation. The data are transferred to VOSviewer software to generate maps and identify key themes in the field of research.

The results of the analysis reveal that each cluster is associated with a distinct keyword, highlighting the research direction on the subject. This gap in research can serve as a case study for the importance of further exploring "Computational Fluid Dynamic & Neural Network". To enhance the accessibility and accuracy of the database, it is recommended to expand the usage of keywords and compare findings from other bibliometric analyses, such as BibExcel and HistCite. Additionally, due to the limited research on fluid dynamics education in machine learning, there is a need for more related research to provide a comprehensive understanding of the field. This research offers important insights into the current state of Neural Network research and provides direction for future research endeavours.

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