Research Trends and Applications of Data Augmentation Algorithms

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1 Introduction

Why is data augmentation important?

What is it used for?

Jürgen Schmidhuber's group shows that a simple MLP architecture can achieve state-of-the-art performance on computer vision benchmarks given strong enough data augmentation [1,2].

[1] Better digit recognition with a committee of simple Neural Nets. Meier, Cires, Gambardella and Schmidhuber 2011 [PDF]

[2] Handwritten Digit Recognition with a Committee of DeepNeural Nets on GPUs. Ciresan, Meier, Gambardella and Schmidhuber 2011 [PDF]

But that was 10 years ago, what about now?

Discuss the importance of those two Google Brain research papers.

2 Theory

Discuss top papers found in the results section.

Heuristic data augmentation algorithms - Oversampling techniques - Image classification techniques

Neural Network-based algorithms

Other types of algorithms, like bayesian-based approaches?

3 Methodology

In this section we describe the procedures defined for the literature collection, data preprocessing and literature analysis. The analysis of the literature was developed with 3 different approaches. Throughout the analyses, data preprocessing and hyperparameter tuning was developed iteratively. The procedure adopted in this manuscript is shown in Figure 1.

The literature collection procedure is described in Subsection 3.1. The data and text preprocessing is described in Subsection 3.2. The exploratory data analysis described in Subsection 3.3 was done to understand which manuscripts, journals and conferences are most significant within the field of Data Augmentation. The manuscripts' keywords were used to construct a network of keywords (described in Subsection 3.4) and study the different communities of keywords found in the network. The topic modelling and parameter tunning is described in Subsection 3.5. The abstract embeddings procedure is described in Subsection 3.6.

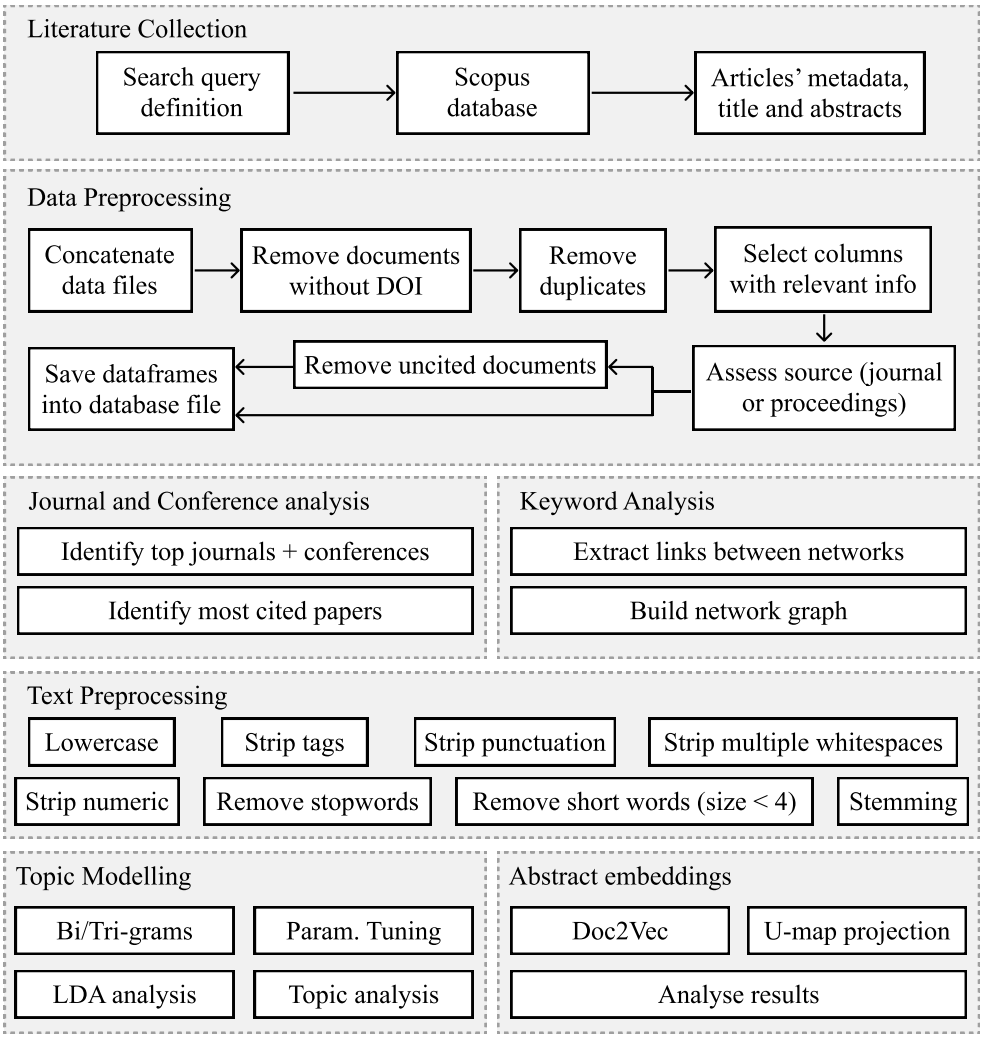

Figure 1: Diagram of the proposed literature analysis approach.

3.1 Literature Collection

The focus of this literature analysis is to understand the different algorithms, domains and/or tasks that employ data augmentation techniques. Therefore, we search for documents containing the keyword "data augmentation" in the search query. The results were then limited to conference papers and journal articles written in English that were published in the past 15 years. Due to the large amount of results found, using solely the Scopus database was found to be sufficient. One of the goals during the search query design was to come up with a simple and unbiased query. The resulting query is shown below:

```
KEY ( "data augmentation" )  AND  ( LIMIT-TO ( LANGUAGE ,  "English" ) )
AND ( LIMIT-TO ( DOCTYPE ,  "cp" )  OR  LIMIT-TO ( DOCTYPE ,  "ar" ) )
AND (
        LIMIT-TO ( PUBYEAR ,  2021 )  OR  LIMIT-TO ( PUBYEAR ,  2020 )
    OR  LIMIT-TO ( PUBYEAR ,  2019 )  OR  LIMIT-TO ( PUBYEAR ,  2018 )
    OR  LIMIT-TO ( PUBYEAR ,  2017 )  OR  LIMIT-TO ( PUBYEAR ,  2016 )
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)
```

The search query resulted in 4281 documents. The resulting data selection/filtering pipeline is shown in Figure 2. Due to the limitations in the Scopus data export (maximum 2000 documents per export), the data was split in four different time periods and exported separately: 2006 until 2018, 2019, 2020 and 2021, which produced four CSV files.

3.2 Data Preprocessing

The data preprocessing stage and amount of documents dropped is represented in Figure 2. The data was first concatenated into a single data frame. During this process, we found that one of the exported references had a corrupted line, which caused the loss of one additional document. Since the DOI can be used as a unique identifier for intellectual property [1], references without a DOI were disregarded from further analysis, while the ones with the same identifiers are removed (*i.e.*, only one of the repeating entries is kept).

This dataset was kept to perform the analysis described in Subsection 3.3. However, further preprocessing was done for the remaining parts of the literature analysis. References without any citations were excluded for the keyword network and topic modelling analyses. Finally, only the documents containing keywords in Scopus' database were used to prepare the network analysis.

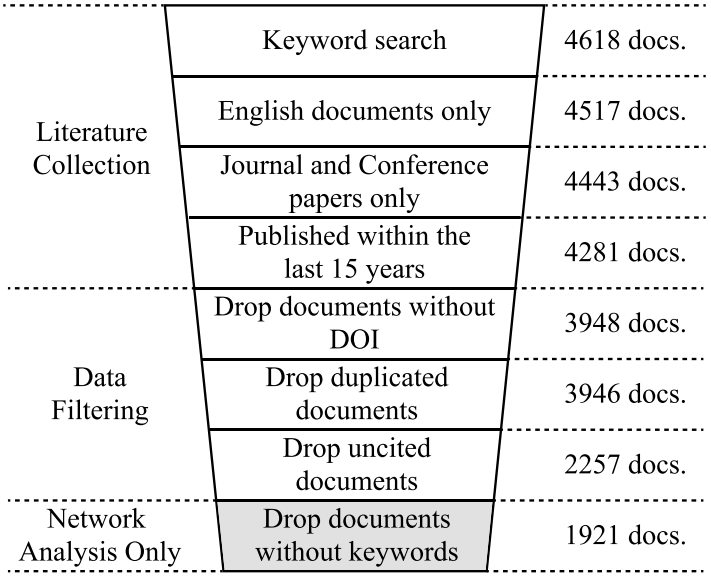

Figure 2: Data filtering pipeline.

3.3 Journal and Conference analysis

The exploratory analysis developed on the preprocessed dataset was targeted towards the identification of the most significant works, journals and conferences. We used the citation count as a proxy to understand the impact of a specific manuscript within the research community.

The identification of the most significant conferences and journals is done by sorting each type of publication according to the number of citations per document. Conferences and journals with less than 10 papers published in the area are not considered in this analysis.

3.4 Keyword Analysis

The analysis of keywords is expected to uncover general trends in data augmentation research and its applications. The keyword "data augmentation" was removed since it would link with all other keywords. Keywords are connected based on their co-occurrence in each research paper to form the edges of the network. It consists of an undirected graph whose weights are based on the total citation count for the papers containing a given keyword pair and is calculated as weight $= \log(\text{citations}) + 1$ to avoid a potential bias caused by highly cited research articles. The size of the nodes were determined with a logarithmic transformation of each node's page rank.

Keyword combinations showing up in only one document are removed from further analysis. The keyword network is then analysed using Python and the communities were found using the greedy modularity

maximization algorithm proposed in [2]. The results of the analysis and community detection were ported to Gephi to produce the final visualizations.

3.5 Topic Modelling

The extraction of topics was done using the publication's abstracts. The words were tokenized and all tags, special characters, punctuation, multiple white spaces, numeric values, stop words and words with size smaller than 4 were removed. Finally, we enriched the corpus by constructing bi-grams and tri-grams.

We used a Latent Dirichlet Allocation (LDA) model [3] to infer the topics present in our research domain. The tuning of the parameters was done through experimentation and qualitative interpretation of the results achieved. Additionally, the coherence score curve was also used as a reference for parameter tuning and the choice of parameters, which are described in Table 1.

3.6 Abstract embeddings

The embeddings of the abstracts was done using the Doc2Vec algorithm [4] and the hyperparameters are defined in Table 1. This allowed the representation of the corpus in a 25 dimension space and was further reduced using a U-map [5] to allow the visualization of the output in a 2-dimensional space.

Model	Hyperparameter	Value
LDA	Num Topics	8
	Chunk Size	2000
	Passes	20
	Alpha	0.1
	ETA	auto
Doc2Vec	Size	25
	Iterations	100
	Min count	10

Table 1: Hyperparameters used.

3.7 Software Implementation

The analysis and modelling was developed using the Python programming language, along with the Scikit-Learn [6], Gensim [7], Umap-Learn [5] and Networkx [8] libraries. The final network analysis and

visualization was done with Gephi [9]. All functions, algorithms, analyses and results are provided in the GitHub repository of the project.

4 Results & Discussion

The popularity of research in data generation has grown significantly in the past 5 years, as shown in Figure 3. Despite the significant amount of uncited publications, out of the ones published in 2020, 39% have already been used in other works. Although most of the research developed before 2016 was used in other works, the amount of cited research increased significantly after that period.

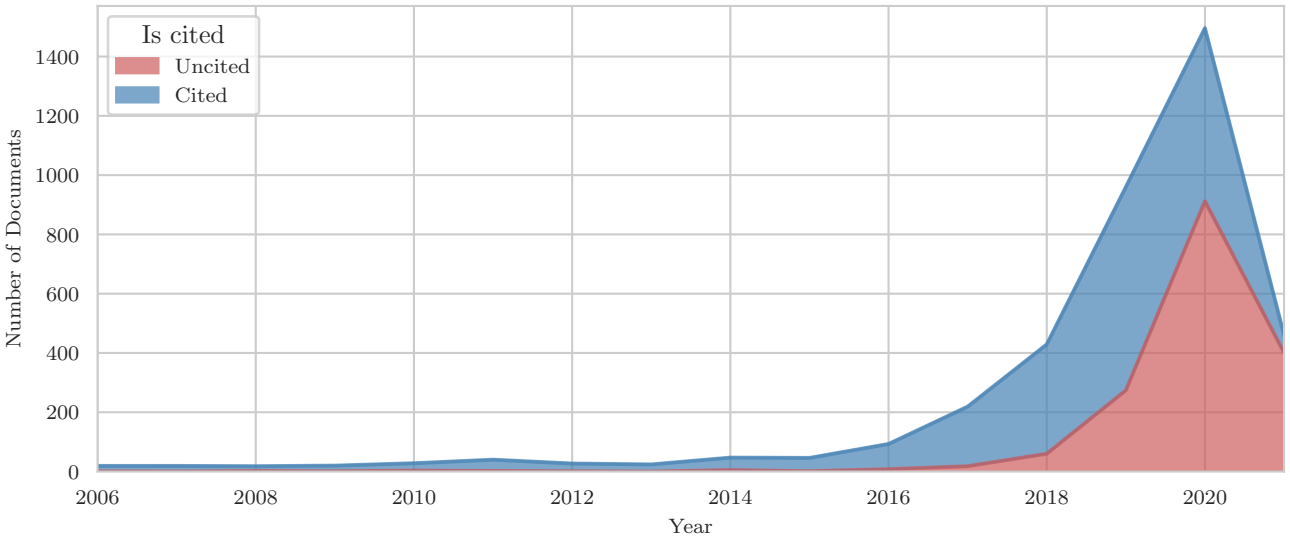

Figure 3: Annual number of publications containing the keyword "data augmentation".

4.1 Journal and Conference Analysis

The initial exploration of the bibliometric data allows us to assess which journals focused in data augmentation more intensely over the past years, as shown in Figure 3. Most of the top journals belong to technical fields, predominantly from Statistics, Remote Sensing, Medical Imaging and other domains of applications such as agriculture. In addition, all these journals have a high impact in their respective fields (based on Scimago Journal & Country Rankings).

Source title	Publications	Citations	Average
Journal of the American Statistical Association	11	538	48.91
IEEE Geoscience and Remote Sensing Letters	19	552	29.05
Neurocomputing	35	808	23.09
Expert Systems with Applications	14	283	20.21
Medical Image Analysis	15	288	19.20
Neural Networks	10	190	19.00
Journal of Computational and Graphical Statistics	23	433	18.83
Computers and Electronics in Agriculture	15	219	14.60
Biometrics	13	163	12.54
IEEE Transactions on Medical Imaging	10	123	12.30

Table 3: Top journals focusing on data augmentation techniques, sorted by citations per document.

Citation-wise, the publications coming from conference proceedings tend to have a comparable impact in the research community, as shown in Table 5. The most relevant conferences are positioned in the computer science and information management fields. Research developed in other areas of application, such as computer vision, speech recognition, acoustic modelling, natural language processing and signal processing have more activity in the form of conference proceedings publications. Conversely, the domains most frequent in journal publications are not as active on conference proceedings publications.

Source title	Publications	Citations	Average
Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition	49	2111	43.08
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	372	14946	40.18
Procedia Computer Science	13	288	22.15
International Conference on Information and Knowledge Management, Proceedings	10	180	18.00
IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops	23	314	13.65
ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings	95	1153	12.14
Proceedings - International Symposium on Biomedical Imaging	30	346	11.53
Proceedings of the International Conference on Document Analysis and Recognition, ICDAR	17	158	9.29
Proceedings of International Conference on Frontiers in Handwriting Recognition, ICFHR	13	113	8.69
2019 IEEE Automatic Speech Recognition and Understanding Workshop, ASRU 2019 - Proceedings	12	84	7.00

Table 5: Top conferences focusing on data augmentation techniques, sorted by citations per document.

The papers with the highest citation count are listed in Table 7. Most of these papers are also discussed in Section 2. We found that much of the research focused on improving deep learning classification, segmentation or object detection without a focus on a particular domain of application. Other papers centered in the application of data augmentation methods for biomedical image classification and segmentation, sound and speech recognition and remote sensing.

Authors	Title	Year	Cited by
Ronneberger O., Fischer P., Brox T.	U-net: Convolutional networks for biomedical image segmentation	2015	13597
Chatfield K., Simonyan K., Vedaldi A., Zisserman A.	Return of the devil in the details: Delving deep into convolutional nets	2014	1885
Snyder D., Garcia-Romero D., Sell G., Povey D., Khudanpur S.	X-Vectors: Robust DNN Embeddings for Speaker Recognition	2018	636
Shorten C., Khoshgoftaar T.M.	A survey on Image Data Augmentation for Deep Learning	2019	590
Salamon J., Bello J.P.	Deep Convolutional Neural Networks and Data Augmentation for Environmental Sound Classification	2017	505
Eitel A., Springenberg J.T., Spinello L., Riedmiller M., Burgard W.	Multimodal deep learning for robust RGB-D object recognition	2015	352
Ding J., Chen B., Liu H., Huang M.	Convolutional Neural Network with Data Augmentation for SAR Target Recognition	2016	319
Wong S.C., Gatt A., Stamatescu V., McDonnell M.D.	Understanding Data Augmentation for Classification: When to Warp?	2016	302
Frid-Adar M., Diamant I., Klang E., Amitai M., Goldberger J., Greenspan H.	GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification	2018	296
Bilen H., Vedaldi A.	Weakly Supervised Deep Detection Networks	2016	287

Table 7: Top papers using data augmentation techniques, sorted by citation count.

4.2 Keyword Analysis

The keyword network shown in Figure 4 revealed 8 main communities of keywords, and 13 other small communities. The different communities are distinguished by the type of algorithms used and/or the domain of application. The main distinctive factor for the larger communities are the types of generative models used, while the smaller communities are distinguished according to the domain of application. The most significant findings we found from this analysis are:

1. The community marked with pink-colored nodes is characterized by the usage of neural network-based data augmentation methods in convolutional neural networks. The keyword "deep learning" is positioned as a central node (although not labelled in the figure to maintain readability). Other relevant keywords are related to machine/deep learning frameworks, deep learning classifiers and data augmentation algorithms, such as "tensorflow", "keras", "convolutional neural network" and "generative adversarial networks". Domain specific keywords are also present:

- Medical keywords located in this community cover a variety of applications. Relevant sub communities are ["hand writing", "parkinson's disease (pd)", "transfer learning"], ["breast cancer", "computer-aided detection"], ["melanoma", "skin cancer", "image processing", "googlenet"], ["chest x-ray", "computer-aided diagnosis", "tuberculosis", "segmentation"] and ["brain", "mri", "multiple sclerosis"].

- Remote sensing keywords are typically related to classification and object detection tasks. Relevant sub communities are ["object detection", "aerial image", "drone", "generative adversarial network", "semantic segmentation"], ["attributed scattering center (asc)", "synthetic aperture radar (sar)", "convolutional neural network (cnn)"], ["remote sensing", "road extraction", "transfer learning", "generative adversarial network"]. Keywords such as "hyperspectral imaging" and "weather classification" are also scattered around the community.

- Facial recognition research is also represented in few sub communities: ["micro expression recognition", "small training data", "convolutional neural network (cnn)", "local binary pattern-three orthogonal planes (lbp-top)"] and ["training data augmentation", "sequence-to-sequence speech synthesis", "sequence-to-sequence speech recognition"].

- Fault detection studies also used data augmentation to deal with imbalanced datasets: ["fault diagnosis", "imbalanced data", "gan"]

- Data augmentation was also associated to regularization methods and feature extraction tasks, based on the presence of the sub communities ["overfitting", "dropout" and "cnn"] and ["feature extraction", "cnn", "svm"].

2. The community marked with blue-colored nodes is characterized by the usage of Markov Chain-based algorithms. The keywords "markov chain", "data augmentation algorithm" and "monte carlo" appear as central nodes. No application-specific sub-community was found.

3. The community marked with green-colored nodes is characterized by the usage of Markov Chain and Bayesian-based algorithms. The keywords "bayesian inference", "markov chain monte carlo", "mcmc", "bayesian analysis", "missing data" and "em algorithm" (expectation maximization algorithm). Application-specific keywords may be found sparsely distributed across the community, all of them related to biological applications. Specifically, the sub community ["ecological health", "stressor-response", "biological monitoring", "bayesian methods"] and the keyword "camera trapping" were found in this community.

4. The community marked with orange-colored nodes is characterized by keywords specific to big data and data warehousing applications. The network is composed of the keywords "big data", "data lake", "olap", "map reduce", "cmm", "data warehouse", "augmentation" and "dm".

5. The remaining communities consist mostly of data augmentation methods applied to specific domains. Specifically, the usage of temporal-dynamic neural network architectures with "eeg (electroencephalogram)", music information retrieval applications (e.g., "chord recognition"), speech/speaker recognition and embedding, time series forecasting of diabetes and natural language processing and text classification.

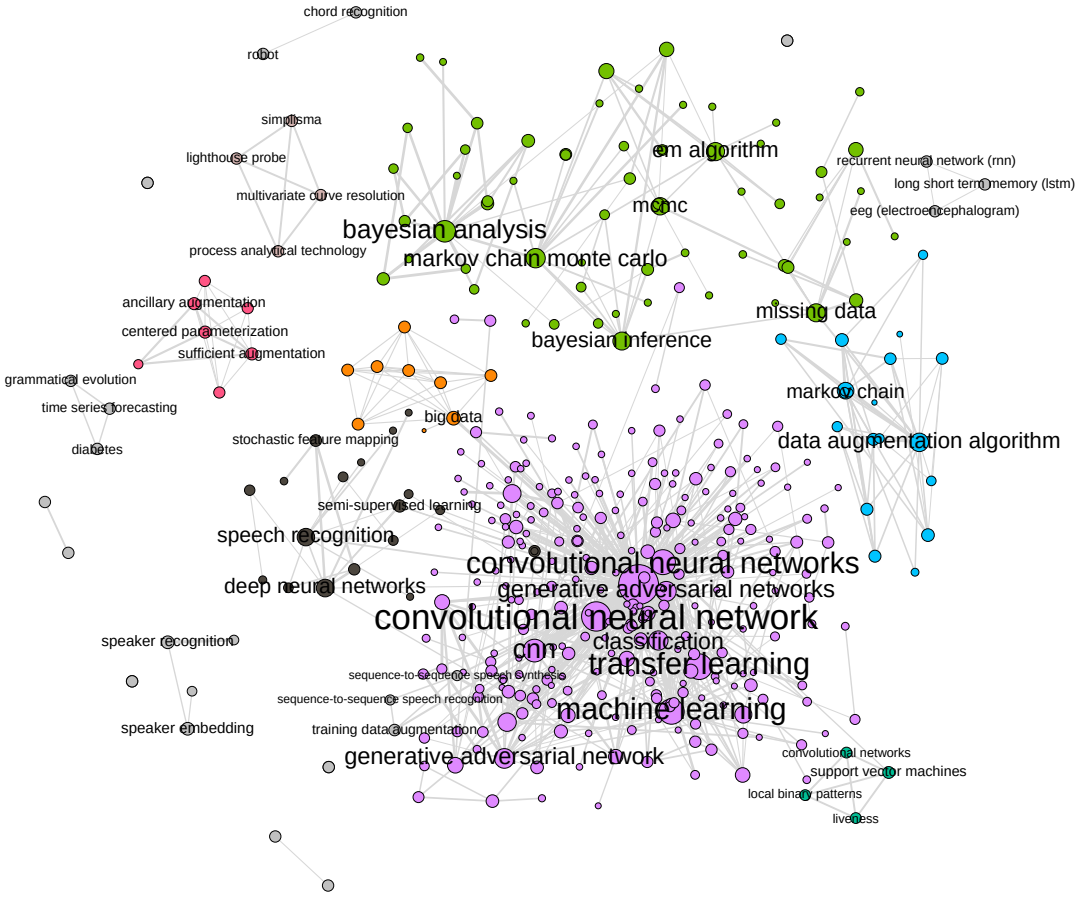

Figure 4: Keyword network.

4.3 Topic Analysis

The LDA topic extraction resulted in 8 different topics, and the distribution of topics is shown in Figure 5. The main topics within which most articles were included is topic 5, is defined by the main theoretical keywords related to image data augmentation. Rather, the secondary topic is more useful for this analysis. It is found based on each document's compatibility with the topic, excluding the most likely topic.

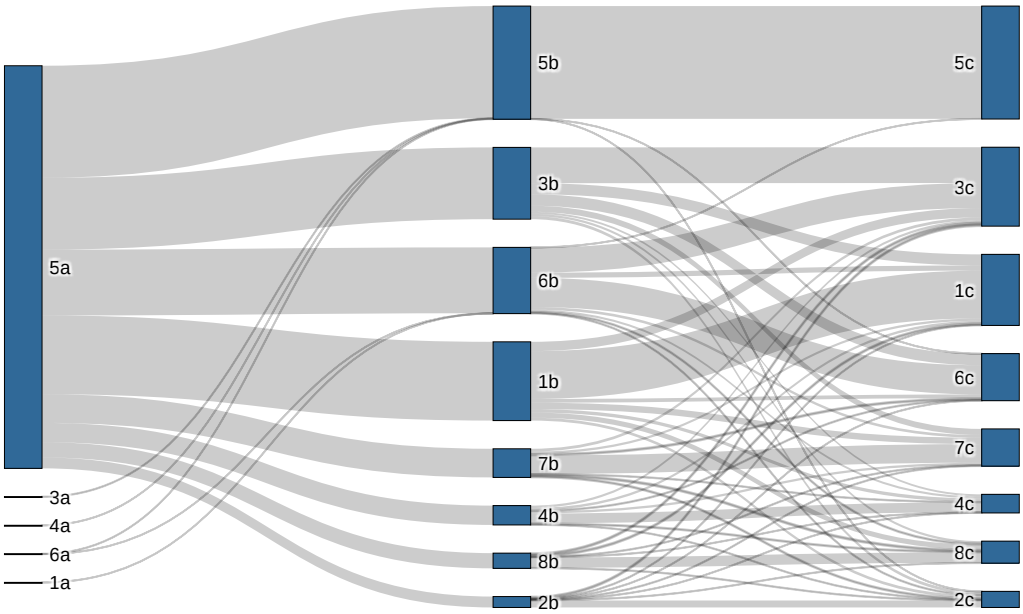

Figure 5: Distribution of documents over the different topics found. The left column represent the primary topics, the middle column represents the secondary topics and the right columns represents the tertiary topics.

The topics found in the bibliometric data are shown in Table 9. A few topics seem to overlap each other, although they are generally distinguishable. The primary domains of application of data augmentation methods differ for each different topic identified.

Topic	Representative Paper	Papers	Words
1	GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification	440	yolov, pest, style_transfer, coffe, thermal, biomed, scene_text, histolog, nodul, visibl
2	CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training	61	hyperspectr_imag, licens_plate, command, inpaint, illumin_chang, upper, restor, ann, foreign, shadow
3	A survey on Image Data Augmentation for Deep Learning	401	censor, markov_chain, node, team, tree, cxr, risk_factor, mass, largest, sourc_separ
4	Return of the devil in the details: Delving deep into convolutional nets	108	smoke, pedestrian, transcrib, crowd, children_speech, intent, adult, auxiliari_variabl, speech, angiographi
5	U-net: Convolutional networks for biomedical image segmentation	632	imag, detect, gener, dataset, classif, sampl, network, cnn, featur, augment
6	Deep Convolutional Neural Networks and Data Augmentation for Environmental Sound Classification	370	tea, multivari, markov_chain_mont_carlo, bayesian, regress, misclassif, procedur, famili, illustr, mcmc
7	Weakly Supervised Deep Detection Networks	160	music, fish, marin, gender, vocal, random_eras, low_qualiti, crowd, prune, bengali
8	An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare	85	drone, gait, aircraft, gestur_recognit, pneumonia, chest_rai_imag, covid, walk, onset, hidden_layer

Table 9: Description of the main topics found in the literature.

The per-year popularity of the different topics is shown in Figure 6. Since 2015, topic 5 gained more research momentum, whereas topic 6 lost much of its relative popularity within the field. In the past 5 years topics 8 and 3 have become steady research streams while topic 1 saw a significant growth in popularity.

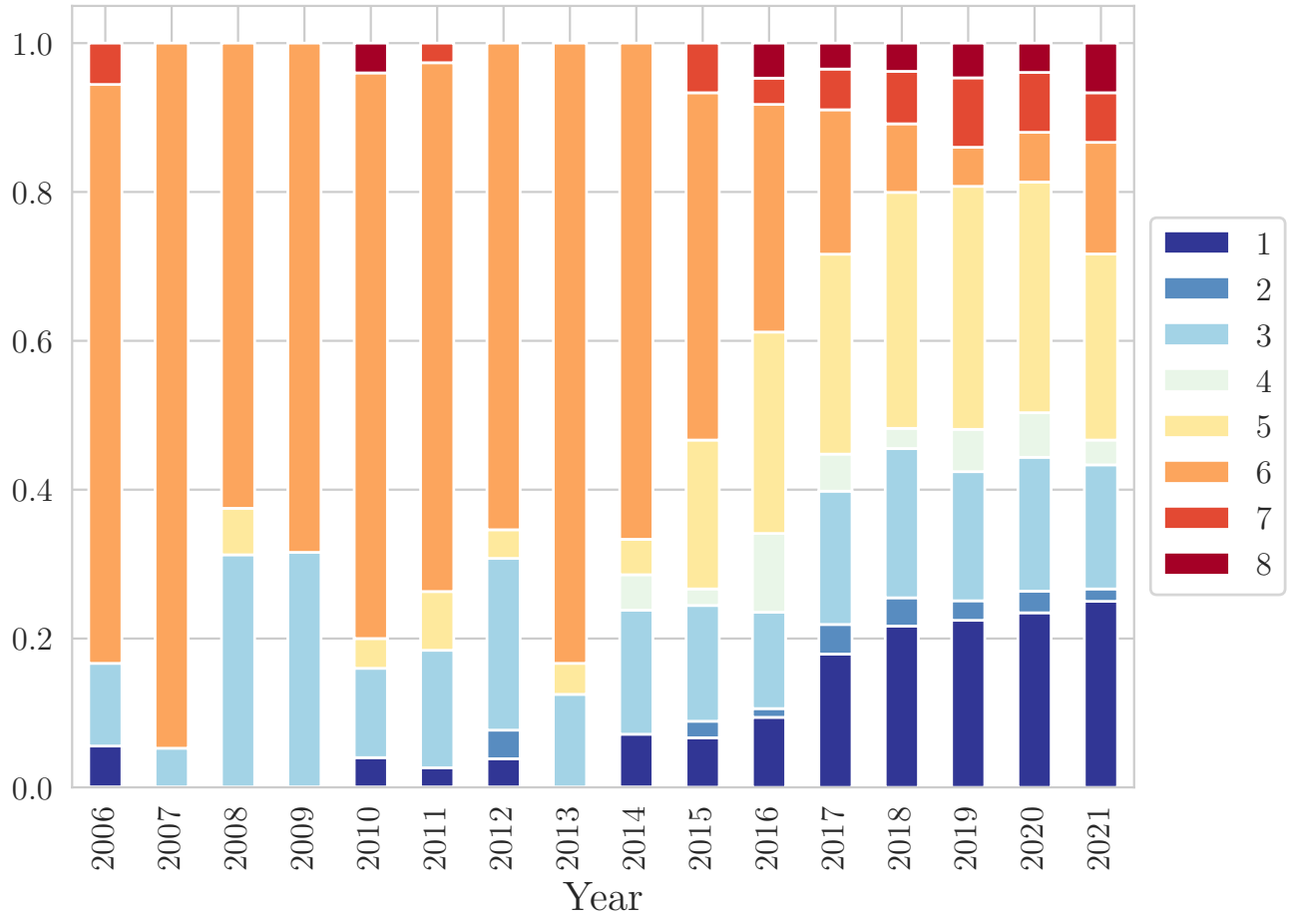

Figure 6: Topic frequency per year.

4.4 Research Question Discussion

4.5 Research Gap Discussion

4.6 Study Limitation Discussion

5 Conclusions

Depending on the domain of application, data augmentation research differs in the format of publication. On the one hand, domains like Statistics, Remote Sensing and Medical Imaging seem more active on journal publications, typically in journals with high impact factor. On the other hand,

References

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