Transfer learning for non-image data in clinical research: a scoping review protocol

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Abstract

Objective:

The objective of this scoping review is to explore and characterize studies using transfer learning for non-image data in clinical research.

Introduction:

Transfer learning is the use of a pre-trained model for a task different to what it was originally trained for. The method has garnered considerable attention in recent years, especially in computer vision and natural language processing. However, despite the increasing interest in machine learning among clinical researchers, the use of transfer learning is not well studied in the medical literature, especially for non-image data.

Inclusion criteria:

We will include clinical studies, published in English in the medical literature, that used transfer learning (fine-tuning or feature-representation transfer) for the analysis of non-image data (e.g. tabular, time series, text, audio). Studies using synthetic data of these types will also be included if they represent or are based on human participants.

Methods:

We will search PubMed, EMBASE and CINAHL for peer-reviewed articles (original articles and brief reports). Each abstract/full-text article will be screened by at least two independent reviewers. Study characteristics will be extracted using a piloted data extraction form. Results will be presented using descriptive statistics and visualizations.

Introduction

The FAIR Guiding Principles urge researchers and stakeholders to enhance the reuse of scientific data. If we go one step further, we could argue that not only data, but also results should be reused more often. Transfer learning is the use of a pre-trained model for a task different to what it was originally trained for (1).

According to Jeremy Howard, founder of fast.ai and a lead figure in the artificial intelligence (AI) community, transfer learning is by far the most important field in AI research. He introduced the idea of transfer learning to natural language processing (NLP), which led to ~20% improved error rate on standard text classification tasks compared to state-of-the-art algorithms at that time (2). Applications are also common in computer vision, where large datasets are publicly available (e.g. ImageNet) to train models that can be then adapted to different domains.

A recent scoping review identified around a hundred articles applying ImageNet-based models (from non-medical domains) and transfer learning to medical image analysis (3). The authors also reported that the number of articles approximately doubled every year between 2016 and 2019. Another review on transfer learning for medical image analysis suggested a similar trend already between 2012 and 2017, demonstrating an increasing interest in the topic in the last 10 years (4). Both reviews focused on images, while tabular and time series data dominates clinical research. Another limitation is that most of the articles were published in computer science journals that assume significant technical knowledge from the readers, making the results less accessible to clinicians and clinical researchers.

Our objective is to explore and characterize studies using transfer learning for non-image data in clinical research.

Scoping reviews serve to identify available evidence, examine research practices and characterize attributes related to a concept (i.e. transfer learning) (5). Therefore, we chose to conduct a scoping review instead of a 'traditional' systematic review.

Review questions

1. **To what extent is transfer learning used in clinical research?**
2. What is transfer learning used for? (e.g. improve predictions or make them feasible)
3. In which areas of clinical research is transfer learning used?
4. Who uses transfer learning? (computer scientists/clinicians/together)
5. Where are the results published? (clinical/interdisciplinary journals)
6. What type of non-image data is transfer learning applied for? (e.g. tabular, time series, text, voice)
7. What are the sizes of the datasets used in transfer learning (both in the source and target domains)?
8. What kind of models are reused with transfer learning? (e.g. CNN, LSTM)
9. Are the reused models and implementation code publicly available?
10. What software was used to implement transfer learning? (e.g. Python, R, MATLAB)
11. Is the transfer learning solution compared to a (benchmark) solution without transfer learning? If yes, what are the costs or benefits of transfer learning?
12. Trend in using transfer learning? (calendar year)

Keywords
clinical prediction; clinical research; deep learning; machine learning; transfer learning

Eligibility criteria

Participants

Studies analysing data from human participants (clinical studies) or synthetic data representing human participants will be considered.

Concept

We will consider studies using transfer learning according to the definition by Howard & Gugger: ‘the use of a pre-trained model for a task different to what it was originally trained for’ (6). This approach is also called network-based transfer learning when the pre-trained model is a neural network (7). We will refer to the original task as the task in the source domain, while the new task as the one in the target domain. We will consider both:

1. parameter transfer, when part of the model trained on the source domain is reused and fine-tuned for a task in the target domain;
2. feature-representation transfer, when (part of) the source model is used in the target domain to extract features (e.g. from a middle layer of a neural network), and those features are then included in a newly developed model, which does not necessarily need to be of the same type as the source model (8).

We will not consider methods that require the actual data from the source domain (even if that is openly available) instead of the source model, because sharing clinical data often presents a barrier in the scientific process due to strict privacy regulations.

Studies will be included if the tasks in the source and target domains are the same and the purpose of using transfer learning is to increase model performance or to make the use of machine learning feasible in a smaller sample. The smaller sample might be a subsample of the dataset in the source domain as demonstrated in previous studies, but only if the developed model is re-used and not the entire dataset data (9, 10).

Context

This scoping review focuses on studies in the clinical research context (studies dealing with clinical outcomes, or clinically relevant biomarkers or measures), regardless of the geographical location, ethnic and gender composition of the study populations.

Methodological articles including any clinical outcome or feature will be included.

Basic research, animal studies and biomedical studies (e.g. cell and molecular biology, biochemistry) will be excluded.

Studies analysing images (also videos as they are considered as sequences of images) will not be considered. However, studies transforming data from other data types (e.g. time series) to images before applying image models will be included.

Types of Sources

This scoping review will consider peer-reviewed articles (e.g. original articles, brief reports) written in English regardless of their study design. Preprints and conference abstracts will not be considered. Reviews will not be included, but relevant ones will be ‘flagged’ during the screening process as they might contribute to the discussion and the identification of articles.

We will only search medical databases that clinical researchers are likely to use (PubMed, EMBASE, CINAHL). Therefore, we will not consider those with a more technical focus (e.g. ACM Digital Library, IEEE Xplore Digital Library).

Inclusion	Exclusion
• Clinical studies (incl. methodological studies with examples using clinically relevant outcomes, measures) • Real/synthetic data from/representing human participants • Studies using transfer learning in the form of re-using pre-trained models with either parameter (weight) transfer or feature-representation transfer • Peer-reviewed published articles (e.g. original articles, brief reports; conference proceedings will be considered if they are peer-reviewed full articles)	• Basic research, animal studies, etc. • Studies using actual data (and not only a model) from the source domain, except if the target domain is a subset of the source domain and a source model is re-used in this subset (e.g. if a model is developed in a sample and then fine-tuned for an individual from that sample, then the study is NOT excluded) • Analyses of image data (also video), except for studies transforming data (e.g. time series) to images as a step of the analysis • Review articles, conference abstracts, preprints

Methods

The proposed scoping review will be conducted in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews and the Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for scoping review (PRISMA-ScR) guidelines (11-13).

Search strategy

The search strategy was designed with the help of an experienced librarian from the Royal Danish Library to identify published, peer-reviewed evidence. AE conducted the search on 18th of May 2021. The detailed search strategy and results are included in Appendix I.

We will share the protocol on social media (e.g. Twitter), and ask readers to notify us about studies that match our inclusion criteria.

Study/Source of Evidence selection

Following the search, all identified citations were collated and uploaded into EndNote (version 20, Clarivate Analytics, PA, USA) and duplicates were removed (see Appendix I). Remaining abstracts were imported into Covidence (Veritas Health Innovation, Melbourne, Australia).

In the screening phase, two independent reviewers will screen title and abstract to assess eligibility. During the planning of the project, the screening phase was tested in a pilot test with 40 randomly selected abstracts. Next, full text versions of potentially relevant articles will be retrieved and assessed in detail against the inclusion criteria by two or more independent reviewers. Reasons for exclusion of sources of evidence at full text screening will be recorded and reported in the scoping review. Any disagreements that arise between the reviewers at any stage of the selection process will be resolved through discussion. If there is no consensus after this, the senior author (AH) will make the final decision. The results of the search and the study inclusion process will be reported in full in the final scoping review and presented in a PRISMA-ScR flow diagram.

Data Extraction

Data will be extracted from included articles by two or more independent reviewers. Data will be collected using a data extraction instrument that was developed and pilot tested using 10 articles during the planning of the study (see Appendix II). The extracted data will include specific details about the study methods and characteristics relevant to the review questions. The data extraction tool will be revised as necessary during the process of extracting data from each included evidence source. Modifications will be detailed in the scoping review. Any disagreements that arise between the reviewers at any stage of the extraction process will be resolved through discussion. If there is no consensus after this, the senior author (AH) will make the final decision. If appropriate and necessary, authors will be contacted to request missing or additional data.

Data Analysis and Presentation

The identified studies will be described in a tabular format (Draft Table 1). Study characteristics will be aggregated using descriptive statistics and presented graphically. The type of statistics and charts will depend on the number of articles included (e.g. reporting percentages does not make sense in case of very few studies). A narrative summary will accompany the tabulated and charted results and will describe how the results relate to the review's objective and questions.

Draft Table 1 – Characteristics of studies that fulfilled inclusion criteria

Article	Study area	Model (software)	Source data	Target data	Aim of study	Comparison to non-TL
Yildirim O, 2019	Endocrinology	CNN (Python)*	Image	Time series	Detect diabetes based on HR signal	10% higher accuracy
Kushner T, 2020	Endocrinology	NN (MATLAB)#	Time series	Time series	Glucose prediction in type 1 diabetes patients	-

*model and/or #code is publicly available (see appendix); TL: transfer learning

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Conflicts of interest

There is no conflict of interest in this project.

References

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Appendix I: Search strategy and results

Search strategy – TL scoping review

Log

- v 0.1, 5/5-21: first draft on pubmed strategy (AE with feedback from AH)
- v 0.2, 6/5-21: Corrected typos + removed inline * + added “transfer learning” in whole text, i.e. not just in tiab (feedback from AVM, Royal Danish Library)
- v 0.3 12/5-21: Added EMBASE and CINAHL + specified which conference abstracts to exclude from Embase
- v 0.4 16/5-21: Added more variations of “transfer learning” from Pratt 1991+93+96: transfer*, transfer weights, network transfer, and learning by learning (feedback from AH)
- v 0.41 17/5-21: Removed transfer of training (term from psychology) + added full references to the remaining secondary keywords (feedback from AH)
- v 1.00 18/5-21: Final version to be uploaded to FigShare (AVM and MT read it through without further comments)

Search strategy

Databases searched:

- Pubmed
- Embase
- CINAHL

The overall search strategy is to include all papers, which include:

> At least one *primary keyword*
> OR
> at least one *secondary keyword* AND at least one *qualifying keyword*

For Embase, papers tagged as conference abstracts (but not conference papers) will be excluded.

Search terms

	Pubmed	Embase	CINAHL	Comments
Primary keywords				
Transfer learning	"transfer-learn*"	'transfer-learn*'	"transfer-learn*"	
	"transfer learn*"	'transfer learn*'	"transfer learn*"	
Secondary keywords				
TL-related	"transfer of learn*"[Tiab]	'transfer of learn*':ab,ti	(TI "transfer of learn*" OR AB "transfer of learn*")	From Singh, S.P. (1992). Transfer of learning by composing solutions of elemental sequential tasks. Mach Learn 8, 323–339 (1992).
Transfer knowledge	"knowledge transfer*"[Tiab] OR "transfer of knowledge"[Tiab] OR "transfer knowledge"[Tiab] OR "transferring of knowledge"[Tiab]	'knowledge transfer*':ab,ti OR 'transfer of knowledge':ab,ti OR 'transfer knowledge':ab,ti OR 'transferring of knowledge':ab,ti	(TI "knowledge transfer*" OR "transfer of knowledge" OR "transfer knowledge" OR "transferring of knowledge" OR AB "knowledge transfer*" OR "transfer of knowledge" OR "transfer knowledge" OR "transferring of knowledge")	From Pratt, L.Y. (1993). Discriminability-Based Transfer between Neural Networks. Advances in Neural Information Processing Systems 5, 204-211.
Transfer networks	"transfer network*"[Tiab] OR "network transfer*"[Tiab]	'transfer network*':ab,ti OR 'network transfer*':ab,ti	(TI "transfer network*" OR "network transfer*" OR AB "transfer network*" OR "network transfer*")	From Pratt (1993)
Transfer weights	"transfer weight*"[Tiab] OR "transferring weight*"[Tiab] OR "transfer of weight*"[Tiab] OR "weight transfer*"[Tiab]	'transfer weight*':ab,ti OR 'transferring weight*':ab,ti OR 'transfer of weight*':ab,ti OR 'weight transfer*':ab,ti	(TI "transfer weight*" OR "transferring weight*" OR "transfer of weight*" OR "weight transfer*" OR AB "transfer weight*" OR "transferring weight*" OR "transfer of weight*" OR "weight transfer*")	From Pratt, L. Y., Mostow, J., & Kamm, C. A. (1991). Direct transfer of learned information among neural networks Proceedings of the ninth National conference on Artificial intelligence - Volume 2, Anaheim, California.
Transfer of information	"transfer of info*"[Tiab]	'transfer of info*':ab,ti	(TI "transfer of info*" OR AB "transfer of info*")	From Pratt, Mostow & Kamm (1991)
Learning by learning	"learning to learn"[Tiab] OR "learning by learning"[Tiab]	'learning to learn':ab,ti OR 'learning by learning':ab,ti	(TI "learning to learn" OR "learning by learning" OR AB "learning to learn" OR "learning by learning")	Pratt L. & Jennings B. (1996) A Survey of Transfer Between Connectionist Networks, Connection Science, 8:2, 163-184,
Connectionist networks	("transfer*"[Tiab] AND ("connectionist network*"[Tiab] OR "connected network*"[Tiab]	('transfer*':ab,ti AND ('connectionist network*':ab,ti OR 'connected network*':ab,ti	(TI ("transfer*" AND ("connectionist network*" OR "connected network*" OR "connection network*")) OR AB ("transfer*" AND ("connectionist network*" OR "connected network*" OR "connection network*")))	From Pratt & Jennings (1996)

	OR "connection network*"[Tiab]))	OR 'connection network*':ab,ti))		
Qualifying keywords				
Artificial intelligence	"Algorithms"[Mesh]	('artificial intelligence'/exp OR 'machine learning'/exp OR 'algorithm'/exp)	(MH "Artificial Intelligence+")	Pubmed: 'algorithms' includes AI, machine learning and a few related topics CINAHL: AI includes ML and NLP
	"artificial intelligence"[Tiab]	'artificial intelligence':ab,ti	(TI "artificial intelligence" OR AB "artificial intelligence")	
	"neural network*"[Tiab]	'neural network*':ab,ti	(TI "neural network*" OR AB "neural network*")	
	"deep learning"[Tiab]	'deep learning':ab,ti	(TI "deep learning" OR AB "deep learning")	
	"deep-learning"[Tiab]	'deep-learning':ab,ti	(TI "deep-learning" OR AB "deep-learning")	
	"machine learning"[Tiab]	'machine learning':ab,ti	(TI "machine learning" OR AB "machine learning")	
	"machine-learning"[Tiab]	'machine-learning':ab,ti	(TI "machine-learning" OR AB "machine-learning")	
AI-related (information science)	("Data Mining"[Mesh] OR "Electronic Data Processing"[Mesh])	('big data'/exp OR 'decision tree'/exp 'classification algorithm'/exp OR 'data clustering'/exp OR 'structural bioinformatics'/exp)	(MH "Data Mining")	Pubmed: All "AI-related" terms are sub-mesh terms to "information science" (https://www.ncbi.nlm.nih.gov/mesh/68007254) Embase: Headings in Embase are more specific than Pubmed Mesh terms, so the search criteria do not match one-to-one CINAHL: 'Electronic data processing' does not exist as subject heading
	"Computer Simulation"[Mesh]	('computer simulation'/exp)	(MH "Computer Simulation")	
	"Data Science"[Mesh]	('data science'/exp)	(MH "Data Science")	
	"Signal Processing, Computer-Assisted"[Mesh]	('wavelet analysis'/exp)	(MH "Signal Processing, Computer Assisted")	
	"Pattern Recognition, Automated"[Mesh]			Embase: Pattern recognition is a cognition-related heading. CINAHL: No similar subject heading
NLP-related	"Word Processing"[Mesh]	('natural language processing'/exp)	(MH "Word Processing")	
	"Speech Recognition Software"[Mesh]	('speech analysis'/exp)		CINAHL: No similar subject heading
	"natural language processing"[Tiab]	'natural language processing':ab,ti	(TI "natural language processing" OR AB "natural language processing")	

Search strings

Pubmed:

("transfer learn*" OR "transfer-learn*")

OR (("knowledge transfer*"[Tiab] OR "transfer of knowledge"[Tiab] OR "transfer knowledge"[Tiab] OR "transferring of knowledge"[Tiab] OR "learning to learn"[Tiab] OR "learning by learning"[Tiab] OR "transfer network*"[Tiab] OR "network transfer*"[Tiab] OR "transfer of info*"[Tiab] OR "transfer of learn*"[Tiab] OR "transfer weight*"[Tiab] OR "transferring weight*"[Tiab] OR "transfer of weight*"[Tiab] OR "weight transfer*"[Tiab] OR ("transfer*"[Tiab] AND ("connectionist network*"[Tiab] OR "connected network*"[Tiab] OR "connection network*"[Tiab])))

AND ("Algorithms"[Mesh] OR "Computer Simulation"[Mesh] OR "Data Science"[Mesh] OR "Pattern Recognition, Automated"[Mesh] OR "Signal Processing, Computer-Assisted"[Mesh] OR "Speech Recognition Software"[Mesh] OR "Word Processing"[Mesh] OR "artificial intelligence"[Tiab] OR "deep learning"[Tiab] OR "deep-learning"[Tiab] OR "machine learning"[Tiab] OR "machine-learning"[Tiab] OR "natural language processing"[Tiab] OR "neural network*"[Tiab] OR ("Data Mining"[Mesh] OR "Electronic Data Processing"[Mesh])))

Embase:

(('transfer learn*' OR 'transfer-learn*')

OR (('knowledge transfer*':ab,ti OR 'transfer of knowledge':ab,ti OR 'transfer knowledge':ab,ti OR 'transferring of knowledge':ab,ti OR 'learning to learn':ab,ti OR 'learning by learning':ab,ti OR 'transfer network*':ab,ti OR 'network transfer*':ab,ti OR 'transfer of info*':ab,ti OR 'transfer of learn*':ab,ti OR 'transfer weight*':ab,ti OR 'transferring weight*':ab,ti OR 'transfer of weight*':ab,ti OR 'weight transfer*':ab,ti OR ('transfer*':ab,ti AND ('connectionist network*':ab,ti OR 'connected network*':ab,ti OR 'connection network*':ab,ti)))

AND ('artificial intelligence':ab,ti OR 'deep learning':ab,ti OR 'deep-learning':ab,ti OR 'machine learning':ab,ti OR 'machine-learning':ab,ti OR 'natural language processing':ab,ti OR 'neural network*':ab,ti OR ('artificial intelligence'/exp OR 'machine learning'/exp OR 'algorithm'/exp) OR ('big data'/exp OR 'decision tree'/exp 'classification algorithm'/exp OR 'data clustering'/exp OR 'structural bioinformatics'/exp) OR ('computer simulation'/exp) OR ('data science'/exp) OR ('natural language processing'/exp) OR ('speech analysis'/exp) OR ('wavelet analysis'/exp))))

NOT ([conference abstract]/lim)

CINAHL:

(("transfer learn*" OR "transfer-learn*")

OR (((TI "knowledge transfer*" OR "transfer of knowledge" OR "transfer knowledge" OR "transferring of knowledge" OR AB "knowledge transfer*" OR "transfer of knowledge" OR "transfer knowledge" OR "transferring of knowledge") OR (TI "learning to learn" OR "learning by learning" OR AB "learning to learn" OR "learning by learning") OR (TI "transfer network*" OR "network transfer*" OR AB "transfer network*" OR "network transfer*") OR (TI "transfer of info*" OR AB "transfer of info*") OR (TI "transfer of learn*" OR AB "transfer of learn*") OR (TI "transfer weight*" OR "transferring weight*" OR "transfer of weight*" OR "weight transfer*" OR AB "transfer weight*" OR "transferring weight*" OR "transfer of weight*" OR "weight transfer*") OR (TI ("transfer*" AND ("connectionist network*" OR "connected network*" OR "connection network*")) OR AB ("transfer*" AND ("connectionist network*" OR "connected network*" OR "connection network*"))))

AND ((MH "Artificial Intelligence+") OR (MH "Computer Simulation") OR (MH "Data Mining") OR (MH "Data Science") OR (MH "Signal Processing, Computer Assisted") OR (MH "Word Processing") OR (TI "artificial intelligence" OR AB "artificial intelligence") OR (TI "deep learning" OR AB "deep learning") OR (TI "deep-learning" OR AB "deep-learning") OR (TI "machine learning" OR AB "machine learning") OR (TI "machine-learning" OR AB "machine-learning") OR (TI "natural language processing" OR AB "natural language processing") OR (TI "neural network*" OR AB "neural network*"))))

Search results

1 Search & import

Search done by AE 18/5-21

Pubmed: 2,332

Embase: 2,251

CINAHL: 319

Total: 4902 references

2 Semi-automatic removal of duplicates

RIS files imported into Endnote x20 without removing duplicates.

Using the duplication tool and changing the default settings, duplications were removed in these step:

#	Set field preferences:	Compare	References removed
1	Author ; Year ; Title ; Secondary title; Volume ; Pages	For blank authors, compare other fields	129
2	Author ; Year ; Title ; Volume ; Pages	For blank pages compare secondary title	1096
3	Author ; Year ; Secondary title ; Pages	For blank pages or blank author compare title	12
4	Author; Volume; Issue; Pages	Deselect references with blank pages or blank author	20
5	Title; Volume; Issue; Pages	Authors ; Deselect references with blank pages;	74
6	Year ; Title ; Secondary title ; Pages	Authors	1
7	Author ; Year ; Secondary title ; Title	Pages	117
8	Year ; Title ; Secondary title	Authors ; Pages	19
9	Year ; DOI *	Authors; Titles	538
10	Author ; Secondary title	Pages / Abstract	13
11	Title	Pages / Abstract	74
12	Author ; Year *	Title / secondary title / abstract	3
13	DOI *	Author / title / abstract	1

All preferences for duplication search criteria were recommended by AU Library (except if marked by *). Preferences marked by * were selected by AE

After duplicates removal: 2805 references

Appendix II: Data extraction instrument (draft)

Data Extraction Form

Transfer learning for non-image data in clinical research: a scoping review

*Required

Reviewer *

- Mette T
- Adam H
- Andreas E
- Ole EA

Covidence Record ID (#X - Author Year) *

Your answer

First author's last name *

Your answer

Year of publication *

Your answer

Are there any authors from clinical departments? *

E.g. clinical, medical, health etc.

- Yes
- No

Are there any authors from technical departments? *

E.g. computer science, mathematics, biostatistics, technology, engineering

- Yes
- No

Study's field within medicine *

E.g. endocrinology, cardiology, public health

Your answer

Purpose of study *

E.g. prediction of biomarker, classification of patients

Your answer

What type of model is reused with transfer learning? *

This refers to the model developed in the source domain.

- [ ] Fully connected NN
- [ ] Convolutional NN (e.g. AlexNet, ResNet)
- [ ] Recurrent NN
- [ ] Classification tree
- [ ] Random forest
- [ ] Boosting
- [ ] Traditional statistical model (e.g. linear, logistic, Cox regression)
- [ ] Other:

Type of transfer learning *

- ○ Parameter (weight) transfer (fine-tuning)
- ○ Feature-representation transfer
- ○ Other:

In case of 'Feature-representation transfer', what type of model is the final model?

This refers to the model developed in the source domain.

- Fully connected NN
- Convolutional NN
- Recurrent NN
- Classification tree
- Random forest
- Boosting
- Traditional statistical model (e.g. linear, logistic, Cox regression)
- Other:

Notes on the methods

Your answer

Is the source model publicly available online? *

- Yes
- No
- Not clear

Is transfer learning (TL) solution compared to a non-TL solution? *

- Yes
- No

In case of 'Yes', characterize the benefits

E.g. X-times less data to achieve the same performance; shorter running time

Your answer

Data type (target domain) *

Characterize the type of the raw data in the target domain, which might be different from the type in the source domain. E.g. if a CGM time series is turned into images and then an image-based model is used, then still choose 'Time series'

- Tabular
- Text
- Time series (e.g. CGM, ECG)
- Audio

Is the data type different in the source and target domains? *

- Yes
- No

Name (if available) and size of source dataset *

Characterize the dataset used to develop the source model re-used in the article. Note the unit of observations.

Your answer

Size of target dataset *

The actual dataset under study. If there are several different datasets (e.g. in case of more outcomes), then write the smallest.

Your answer

Software used for data analysis *

- [ ] Python
- [ ] R
- [ ] MATLAB
- [ ] SAS
- [ ] Other:

Is the code used to implement transfer learning publicly available online? *

E.g. on GitHub or as an electronic supplement

- ( ) Yes
- ( ) No
- ( ) Not clear

Notes on the article

Your answer

Submit