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Transfer Learning Advancements: A Comprehensive Literature Review on Text Analysis, Image Processing, and Health Data Analytics

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Abstract

This literature review delves into the recent advancements in transfer learning, examining its applications and enhancements across diverse domains. Focused on the conclusions drawn from various studies, the review highlights the evolution of transfer learning in three key areas: text analysis, image processing, and health data analytics. In text analysis, innovations such as BERT, CNN-BiLSTM, AdapterFusion, and T-BERT Framework showcase the ongoing efforts to improve efficiency and adaptability in understanding complex natural language tasks. Similarly, in image processing, the review emphasizes the varied use of pre-trained models, feature extraction techniques, and diversified datasets, leading to enhanced performance in tasks like image classification, object detection, and facial recognition. Furthermore, the application of transfer learning in health data analytics, particularly with CNN models like AlexNet, ResNet, GoogLeNet, and EfficientNet, reflects significant progress in tasks such as MRI brain image classification, skin lesion analysis, brain tumor detection, and other medical image analyses. The advantages of transfer learning, including consistent performance improvement and computational efficiency through the use of pre-trained models, are discussed. However, challenges such as overfitting in specific contexts and the need for careful adaptation in medical data analytics are acknowledged. The review concludes with recommendations for future research directions, urging a focus on improving domain-specific adaptation, exploring multi-modal model integration, enhancing transfer learning for limited health datasets, and investigating its potential for multi-task applications in text, image, and health data analytics. The comprehensive insights provided in this review contribute to the understanding and advancement of transfer learning in the current landscape of artificial intelligence research.

Keywords: *Transfer Learning, Fine-Tuning, Model Pre-Trained, BERT, CNN*

Introduction

Although traditional machine learning technologies have achieved significant success and have been successfully applied in many practical applications, they still have some limitations for certain real-world scenarios (Aslan et al., 2021). The ideal scenario for machine learning is having a large number of labeled training examples that have the same distribution as the testing data. However, in many scenarios, collecting adequate training data is often expensive, time-consuming, or even unrealistic. Semi-supervised learning can partially address this issue by reducing the need for massive labeled data

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(Chen et al., 2020). Typically, semi-supervised approaches only require a limited amount of labeled data and utilize a large amount of unlabeled data to improve learning accuracy. However, in many cases, collecting unlabeled examples is also challenging, often resulting in unsatisfactory models generated by traditional methods (Prottasha et al., 2022).

Transfer learning, which focuses on cross-domain knowledge transfer, is a promising machine learning methodology to tackle the aforementioned problems. The concept of transfer learning may have originally stemmed from educational psychology. According to the theory of transfer generalization, as proposed by psychologist C. H. Judd, the conditions for transfer require a connection between two learning activities. In practice, someone who has learned the violin may learn the piano faster than someone else, as both the violin and piano are musical instruments and may have some similarities (Bansal et al., 2021).

In selecting an algorithm for a transfer learning approach, it is crucial to consider its uniqueness and flexibility. The chosen algorithm should be capable of extracting useful representations from the source task to be adopted for the target task. The success of transfer learning also depends on the algorithm's ability to capture common data structures between the two tasks. Transfer learning is an approach in machine learning where a model trained on one specific task or domain is modified or adapted to address a different, yet related, task or problem (Pathak et al., 2022).

The term "transfer" refers to the fact that knowledge or representations acquired by the model from one task can be "transferred" to another task. Transfer learning is commonly employed when the amount of available data for a new task is limited, but there is ample data available for a similar task. In the context of natural language processing (NLP), an example of transfer learning is using pre-trained language models such as BERT (Bidirectional Encoder Representations from Transformers) or GPT (Generative Pre-trained Transformer) (Qasim et al., 2022). These models are trained on large tasks, such as predicting the next word in a sentence or understanding relationships between words in context, and can then be fine-tuned for specific tasks like text classification, named entity recognition, or language translation.

The primary advantage of transfer learning is the ability to leverage existing knowledge and expedite the model training process for specific tasks (Han et al., 2018). This has contributed to achieving better performance in various machine learning and natural language processing fields. Based on the background description, transfer learning algorithms are relevant to literature studies focusing on text classification, image classification, and cell classification. Research Question: What are the latest technologies applied in the context of transfer learning, and how have these developments enhanced performance and provided significant improvements in transfer learning applications in the last five years?

Method

Following the established systematic literature review method, the review was conducted in different stages. First, the identification of search sources was performed using several keywords developed in relation to Transfer Learning. Second, identification based on inclusion and exclusion criteria was carried out, referring to the process of

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selecting and categorizing literature resources to be included (inclusion) and excluded (exclusion) in the literature review. This method is essential to ensure the relevance, quality, and focus of the ongoing literature review. Third, an in-depth research search was conducted, followed by critical assessment, data extraction, and synthesis of previous findings (Mikalef et al., 2018).

Search Strategy

The first step in conducting a literature review is to identify search sources using relevant keywords for the specified topic. In the context of Transfer Learning, these keywords can aid in finding articles, papers, and other sources of information related to the concept.

1. **Identify Search Sources**: Select appropriate databases or information sources such as IEEE Xplore, ACM Digital Library, Google Scholar, PubMed, arXiv, or Scopus.
2. **Develop Search String**: Create a search string with keywords related to Transfer Learning, such as "Fine Tuning," "Pre-Trained," "Transfer Learning," and the like.
3. **Include Synonyms and Related Terms**: Add synonyms and other related terms to ensure comprehensive coverage, enabling a more thorough exploration of literature during the search.

Inclusion and Exclusion Criteria

Due to the importance of the selection stage in determining the overall validity of the literature review, several inclusion and exclusion criteria were applied.

1. **Inclusion Criteria:** In conducting a literature review on Transfer Learning algorithms, inclusion criteria were established to ensure that the selected literature is directly relevant to the research topic. Firstly, literature search using keywords related to Transfer Learning, such as "Transfer Learning," "Fine Tuning," and "Pre-Trained." The literature should focus o n the applications, improvements, or comparisons of transfer learning. A relevant publication timeframe, specifically the last 5 years, was set to ensure that the obtained information is the most current. The type of publication was also considered, with a preference for reputable scholarly journals such as IEEE Xplore, ACM Digital Library, Google Scholar, PubMed, arXiv, and Scopus. The selection of literature should encompass various contexts of transfer learning applications, such as image processing, natural language processing, or other application domains. Lastly, the type of research, whether it is experimental, qualitative, or theoretical, was also a factor for inclusion.

2. **Exclusion Criteria:** While inclusion criteria guide the selection of literature, exclusion criteria are applied to ensure that less relevant or unreliable literature is avoided. Literature that is not directly related to Transfer Learning algorithms or only discusses related topics in a general sense is excluded. Literature that is too old or no longer relevant to recent developments in the field of transfer learning is also excluded or those published more than 5 years ago. Additionally, publications from less well-known journals or conferences with questionable reputations are avoided. Exclusion can also be based on the evaluation of the quality of research methodology, avoiding literature with weak study designs or questionable methodologies.

Quality Assessment

Out of the initially collected articles (around 30) after stage 2, 20 articles were retained based on several quality criteria. Overall, these criteria provide a measure of how much a publication will contribute valuable insights to the review. At this stage, the 20 articles are subjected to data extraction and synthesis. These articles are then coded according to their focus areas, allowing for categorization. By grouping articles based on their categories, the necessary details can be extracted to address the research questions posed.

Data Extraction and Synthesis of Findings

The first step involves identifying the main concepts from each relevant study. These concepts are then organized into a table that allows for a comparison across studies. In this table, each row represents one study, and the columns encompass key concepts or findings to be compared. The table is populated with relevant data from each study, such as research methods, major findings, datasets, or other variables. The use of a table facilitates the comparison of findings across studies and allows for the identification of patterns, similarities, or differences. Subsequently, the synthesis of findings is carried out by summarizing the key findings from each study, identifying common patterns, trends, or contradictions. The results of data extraction and synthesis of findings serve as the basis for drawing conclusions, evaluating research questions, and composing the research report or article. This approach provides a systematic structure for literature analysis and facilitates the process of effectively synthesizing findings.

Results and Discussion

After gathering and categorizing articles based on their concepts, data extraction was performed. The following table presents the literature review on Transfer Learning in various contexts.

Transfer Learning for Text Analysis with Multiple Models and Text Datasets

Table 1. *Transfer Learning for Text Analysis*

Author(s) & date	Model	Dataset
Qasim et al., 2021	BERT-base, BERT-large, RoBERTa-base, RoBERTa-large, DistilBERT, XLM-RoBERTa-base, ALBERT-base-v2, Electra-small, and BART-large	On three datasets related to COVID-19, COVID-19 English tweets, and extremist-non-extremist dataset.
Prottasha et al., 2022	Implemented a CNN-BiLSTM model with BERT transfer learning	Used Bangla language text data for sentiment analysis.
Pfeiffer et al., 2020	AdapterFusion	Employed 16 datasets for natural language understanding.
Alaparthi et al., 2021	T-BERT Framework BERT	Applied on 40,000 raw microblogs without user information.
Wang et al., 2020	Employed Dynamic Distribution Adaptation (DDA) to Manifold Dynamic Distribution Adaptation (MDDA) for traditional transfer learning and Dynamic Distribution Adaptation Network (DDAN) for deep transfer learning	Covered USPS+MNIST, Amazon reviews, Office-31, ImageCLEF DA, and Office-Home with variations in sample size, features, classes, and domain types.

In the literature related to transfer learning in text analysis, various studies have proposed diverse approaches to understand and enhance model performance. Qasim et al. (2021) elucidated the utilization of various models such as BERT, RoBERTa, and the like on COVID-19-related datasets and English tweet data. Prottasha et al. (2022) adopted a CNN-BiLSTM model with transfer learning from BERT in the context of sentiment analysis with Bangla language data. Pfeiffer et al. (2020) developed the AdapterFusion model for natural language understanding using 16 datasets. Alaparthi et al. (2021) introduced the T-BERT Framework and applied the BERT model to raw microblogs without user information. Meanwhile, Wang et al. (2020) explored transfer learning approaches such as Dynamic Distribution Adaptation (DDA) and Dynamic Distribution Adaptation Network (DDAN) on various datasets, including USPS+MNIST, Amazon reviews, and others.

Collectively, these studies reflect significant attention to the application of transfer learning to enhance the performance of text analysis models. Models such as BERT and CNN-BiLSTM are often the focal points for leveraging knowledge from related tasks or more general languages. Additionally, model adaptations like AdapterFusion and the T-BERT Framework demonstrate efforts to design innovative frameworks in natural language understanding. Despite the use of various datasets to test the models, this research indicates that transfer learning can be applied in various contexts, ranging from sentiment analysis to more complex natural language tasks. Overall, this literature highlights a positive trend in incorporating transfer learning to improve the understanding and performance of models in text analysis.

Transfer Learning for Image Analysis Using Different Methods

Table 2. *Transfer Learning for Image Analysis*

Author(s) & date	Model	Dataset
Chakraborty et al., 2022	Efficient Filtering	6.71 million images from Places, OpenImages, ImageNet, and COCO datasets.
Bansal et al., 2021	VGG19 deep learning model. Feature extraction using SIFT, SURF, ORB, and Shi-Tomasi corner	Caltech-101, covering various object categories.
Han et al., 2018	CNNs like AlexNet, VGG, and ResNet, and web data augmentation	Dataset with categories Flowers, Dogs, Caltech-101, Event8, 15 Scene, and 67 Indoor Scene.
Wang et al., 2020	Ranking-based selection, autoencoder usage, and retraining	From VGG-FACE training with 2.6 million images and over 2.6 thousand individuals. External public validation data obtained from LFW (Labeled Faces in the Wild), containing 13,233 images with 5,749 identities.
Sudhakar et al., 2021	MCFT-CNN combining traditional and transfer learning approaches on MalImg dataset and Microsoft Malware Challenge dataset	MalImg and Microsoft Malware Challenge.
Espejo-Garcia et al., 2020	Combining fine-tuning of pre-trained convolutional networks (Xception, Inception-Resnet, VGG-Net, MobileNet, and DenseNet) with traditional machine classification (Support Vector Machines, XGBoost, and Logistic Regression)	Two plants (tomato and cotton) and two weed species (black nightshade and velvetleaf).

In the literature related to transfer learning in image analysis, several studies highlight various strategies and approaches that can be employed to enhance model performance. Chakraborty et al. (2022) leveraged Efficient Filtering using datasets that include images from Places, OpenImages, ImageNet, and COCO. Bansal et al. (2021) focused on the VGG19 deep learning model and applied feature extraction with SIFT, SURF, ORB, and Shi-Tomasi corner on the Caltech-101 dataset. Han et al. (2018) integrated CNNs such as AlexNet, VGG, and ResNet with web data augmentation for image analysis tasks on diverse datasets, including Flowers, Dogs, and Caltech-101. Wang et al. (2020) demonstrated a different approach by combining rank-based selection, autoencoder usage, and retraining on VGG-FACE training with extensive datasets, including external validation data from LFW (Labeled Faces in the Wild). Sudhakar et al. (2021) proposed the MCFT-CNN model that combines traditional and transfer learning approaches, particularly on the MalImg and Microsoft Malware Challenge datasets. Espejo-Garcia et al. (2020) combined fine-tuning pre-trained convolutional networks such as Xception, Inception-Resnet, VGG-Net, MobileNet, and DenseNet with traditional machine classification for plant image analysis (tomato and cotton) and weed species (black nightshade and velvetleaf).

Collectively, this literature indicates that transfer learning plays a significant role in improving model performance in image analysis tasks such as image classification, object detection, image segmentation, face recognition, and more. Diverse approaches include the selection of different pre-trained models, feature extraction techniques, and the utilization of varied datasets. By combining these various approaches, research on transfer learning for image analysis can provide in-depth and comprehensive insights, helping guide further research and development in this field.

Transfer Learning for Health Data Analysis

Table 3. *Transfer Learning for Health Data Analysis*

Author(s) & date	Model	Dataset
Kaur et al., 2022	Model DCNN, pre-trained Alexnet, Resnet50, GoogLeNet, VGG-16, Resnet101, VGG-19, Inceptionv3, and InceptionResNetV2.	Harvard repository with 284 images, clinical dataset from Fortis Memorial Research Institute with 500 images from 200 patients (250 normal and 250 abnormal), and dataset from Figshare containing 3064 brain MRI images from 233 patients with glioma, meningioma, and pituitary tumors.
Baykal et al., 2020	CNN (ConvNets) architectures pre-trained, namely AlexNet, GoogleNet, ResNet, and DenseNet.	Proposed serous cell dataset in 2003. The dataset consists of 3652 images, each containing one serous cell, with 11 classes and sample count for each class.
Mahbod et al., 2020	Three CNN architectures, namely EfficientNetB0, EfficientNetB1, and SeReNeXt-50, explored for skin lesion classification	ISIC 2016, ISIC 2017, and ISIC 2018 challenges. A total of 12,927 skin lesion images were used for training and testing.
Rehman et al., 2019	Three Convolutional Neural Networks (CNN) architectures, namely AlexNet, GoogLeNet, and VGGNet	Publicly available brain tumor dataset from Figshare. Consists of 3064 brain MRI slices from 233 patients with three types of brain tumors, namely meningioma, pituitary, and glioma.
Aslan et al., 2929	Arsitektur AlexNet and Bidirectional Long Short-Term Memories (BiLSTM) layers.	Open chest X-ray image database with 219 images of COVID-19 positive, 1345 images of viral pneumonia, and 1341 normal images, totaling 2905 images with three classes.

Author(s) & date	Model	Dataset
Pathak et al., 2020	ResNet-50 network for feature extraction from COVID-19 chest CT image dataset.	Chest CT images of COVID-19 patients with 413 COVID-19 (+) images and 439 images of normal or pneumonia-infected patients.
Deniz et al., 2018	CNN models like AlexNet and Vgg16 for breast cancer histopathology image classification. Exploration of feature vectors extracted from fc6 and fc7 layers of both models.	BreaKHis dataset consisting of 9,109 histopathological microscopy images, with 2,480 benign and 5,429 malignant images.
Wang et al., 2019	Inception-v3 for pulmonary image classification.	Dataset from the JSRT digital image database covering lung CT images with and without lung nodules.
Chen et al., 2020	Federated transfer learning named FedHealth	UCI Smartphone dataset with 6 activities collected from 30 users with smartphones on their waist. Accelerometer and gyroscope data from 9 channels were collected at a constant rate of 50Hz. FedHealth involves 25 users and 5 isolated subjects.

In research on transfer learning for health data analysis, several studies have explored the application of pre-trained models to enhance the performance of specific health data analysis tasks. Kaur et al. (2022) utilized a DCNN model with pre-trained AlexNet, Resnet50, GoogLeNet, VGG-16, Resnet101, VGG-19, Inceptionv3, and InceptionResNetV2 on clinical datasets from Fortis Memorial Research Institute, Harvard repository, and Figshare dataset containing brain MRI images. Baykal et al. (2020) applied CNN architectures such as AlexNet, GoogleNet, ResNet, and DenseNet on a serous cell dataset comprising 3652 images with 11 classes. Mahbod et al. (2020) explored three CNN architectures, namely EfficientNetB0, EfficientNetB1, and SeReNeXt-50, for skin lesion classification using ISIC 2016, ISIC 2017, and ISIC 2018 challenge datasets. Rehman et al. (2019) utilized three Convolutional Neural Network (CNN) architectures—AlexNet, GoogLeNet, and VGGNet—on a brain tumor dataset from Figshare that includes three types of brain tumors. Aslan et al. (2019) used AlexNet architecture and Bidirectional Long Short-Term Memories (BiLSTM) layers on a chest X-ray image database containing 219 COVID-19 positive images, 1345 viral pneumonia images, and 1341 normal images. Pathak et al. (2020) employed ResNet-50 network to extract features from a CT chest image dataset of COVID-19 with 413 COVID-19 (+) images and 439 images of normal or pneumonia-infected patients. Deniz et al. (2018) implemented CNN models such as AlexNet and Vgg16 on the BreaKHis dataset consisting of 9,109 microscopic histopathological breast cancer images. Wang et al. (2019) used Inception-v3 to classify pulmonary images in a dataset from JSRT. Chen et al. (2020) developed a federated transfer learning named FedHealth on the UCI Smartphone dataset, covering accelerometer and gyroscope data from 6 activities collected from 30 users with smartphones on their waist.

Collectively, this literature indicates that transfer learning is an effective approach for improving the performance of health data analysis. Researchers have applied various CNN models, such as AlexNet, ResNet, GoogLeNet, EfficientNet, and combinations of architectures, to diverse health datasets, including brain MRI image classification, skin lesion analysis, brain tumor detection, chest X-ray image analysis, COVID-19 chest CT image analysis, and pulmonary image classification. The application of pre-trained models on specific datasets illustrates the adaptation required to address the complexity and variability of medical data. Overall, this literature demonstrates that transfer learning can be relied upon as a primary strategy to enhance the performance of health data analysis models through the adaptation and application of pre-trained models on diverse medical datasets.

Conclusion

The latest technology in the application and improvement of transfer learning has seen significant advancements in various contexts. In text analysis, innovation is evident through the utilization of sophisticated models such as BERT, CNN-BiLSTM, AdapterFusion, and T-BERT Framework, with an emphasis on the development of more efficient and adaptive transfer learning methods, particularly for complex natural language tasks. Meanwhile, in image analysis, the use of diverse pre-trained models, innovative feature extraction techniques, and diversified datasets has strengthened the application of transfer learning, resulting in improved performance in image classification, object detection, image segmentation, and facial recognition. In the field of health data analysis, the implementation of CNN models like AlexNet, ResNet, GoogLeNet, and EfficientNet on various datasets has shown significant progress, especially in tasks such as brain MRI image classification, skin lesion analysis, brain tumor detection, and other medical image analyses. Overall, these developments reflect a positive trend in optimizing transfer learning to enhance understanding and model performance across various domains.

Transfer learning brings several significant advantages in model development. One of them is the consistent improvement in model performance, especially in tasks requiring understanding of complex contexts or representations. Another advantage is the computational efficiency resulting from the use of pre-trained models, allowing for savings in computational resources and training time, particularly in the domain of deep learning, which often involves processing large-scale data. The combination of improved performance and computational efficiency makes transfer learning a highly valuable approach in developing intelligent and efficient models.

However, transfer learning is not without its limitations. One of them is the potential for overfitting in highly specific task contexts when the model is trained on general datasets. Models trained on general data may not fully fit or may experience overfitting when faced with tasks that have specific characteristics. Additionally, in the context of health data analysis, transfer learning faces adaptation challenges that need to be carefully managed. The complexity and variation in medical data require careful adaptation strategies to ensure effective model performance on diverse medical datasets.

For future research in transfer learning, the focus should be directed towards several key aspects. Firstly, research can be expanded to enhance domain-specific adaptation, particularly in addressing significant domain differences, as observed in healthcare applications. Developing better transfer learning techniques can assist models in performing optimally in highly specific task contexts. Furthermore, the exploration of combining multi-modal models, involving various modalities such as text, images, and health data, can provide a deeper cross-domain understanding. It is also crucial to continue exploring transfer learning under limited health data conditions, with an emphasis on effective adaptation for diverse datasets. Additionally, research can be focused on the potential of transfer learning for multi-tasking, which can enhance the efficiency and overall performance of models in text, image, and health data analysis simultaneously. The integration of these suggestions can provide a more comprehensive and profound insight into guiding the future development of transfer learning.

Acknowledgment

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