Transfer Learning for Human-like Computing

Aanchal Yadav[1] , Parul Agarwal[1], Suraiya Parveen[1] Sherin Zafar[1]
[1](Department of Computer Science and Engineering, Jamia Hamdard, India)

Abstract: **This review paper explores how transfer learning techniques are applied in the field of human-like computing, which focuses on creating AI systems that mimic human cognitive abilities. We delve into the fundamental concepts of transfer learning and its significance within this domain. Furthermore, we investigate various strategies like fine-tuning, feature extraction, and model adaptation and their effectiveness in tasks related to natural language processing (NLP), computer vision, emotion recognition, speech processing, and cognitive reasoning. By harnessing pre-trained models, AI systems can gain a better understanding of human-like behaviors, enabling more lifelike responses. Additionally, this paper highlights the challenges encountered in applying transfer learning to human-like computing and suggests potential directions for future research to address these challenges. In summary, our review offers valuable insights into the current state of transfer learning within the field of human-like computing, emphasizing the importance of ongoing innovation.**

Keywords: Transfer Learning, Deep Learning, Human-like Computing, Cognitive Modeling, Feature Extraction, NLP.

I. INTRODUCTION

Machine learning's strong notion of Transfer Learning (TL) allows a design that has been trained for one activity to be implemented in other related activities. TL enables models to leverage knowledge acquired from one activity and apply it to another linked or unrelated task. Unlike conventional ML techniques, where algorithms are built from the ground up on specific datasets for a particular objective, TL takes a different approach by utilizing pre-trained models that have been trained on a wide range of databases, typically on a distinct but related task. The main theory behind TL is that the knowledge acquired from solving one task can be transferred and used as a starting point for solving another task. This approach has gained significant popularity due to its ability to overcome the limitations of small and limited datasets. By utilizing pre-trained models, transfer learning allows for the effective transfer of learned representations, enabling models to generalize better, learn faster, and achieve higher performance on new tasks with fewer labeled examples.

In transfer learning, the pre-trained models, often referred to as the "base" or "source" models, have typically been trained on large-scale databases like ImageNet for computer vision tasks or large text corpora for natural language processing tasks. These models have learned general features and patterns that are valuable for many tasks. Instead of starting the training process from scratch, TL involves taking these pre-trained designs and fine-tuning them on a smaller, task-specific dataset, known as the "target" dataset .

There are two basic methods for transferring knowledge: feature extraction and fine-tuning. Feature extraction involves using a pre-trained model to extract relevant features from the input data. These features are then utilized to learn a new model for the target task. Fine-tuning, on the other hand, builds upon a pre-trained model by adjusting its parameters using the target dataset. Fine-tuning allows the model to adapt to the specific nuances of the new task while retaining the valuable knowledge gained from the base model.

The motivation behind this comprehensive exploration of Transfer Learning within the realm of human-like computing lies in the ever-increasing importance of this groundbreaking concept. Our focus in this study is to shed light on the principles, techniques, and applications of Transfer Learning, delving deep into the ramifications it holds for mimicking human learning, cognitive modeling, and problem-solving. The aim is not only provide a profound understanding of Transfer Learning but also uncover its immense potential in advancing human-like computing systems, revolutionizing the landscape of artificial intelligence and machine learning.

The structure of this article is organized as obeys: Section II presents an introduction to the transfer learning techniques employed in the study. Section III explores the existing literature and research conducted in the field of transfer learning in human-like computing. Section IV discusses the significance of transfer learning in human-like computing, delving into the specific types and applications within this domain. Section V addresses the research gaps associated with transfer learning in human-like computing. Lastly, Section VI summarizes the key findings of the paper and offers future research directions in this area.

II. TRANSFER LEARNING TECHNIQUES

TL is a powerful approach that can bein a numberof settings. It is significant to be aware of the various types of TL & to choose the right approach for the specific task at hand.TL could be divided into several types depending on the nature of the source &target tasks, & the approach used to transfer knowledge [6-7]. Here are some common types of transfer learning:

Domain adaptation: It [7] is a kind of TL that is utilized when the source & target tasks are in various domains. For instance, a design that has been learned to identify cars in the real world can be adapted to recognize cars in a video game.

*Multitask learning:*It is a kind of TL that is used when multiple tasks are learned simultaneously. For instance, a designthat has been learned to identify cats and dogs can be used to learn to recognize both cats and dogs.

*Zero-shot learning:*It is a type of TL that is usedwhen there is no labeled information accessible for the target task. For instance, a design that has been learned to identifycats and dogs can be used to learn to recognize a new animal, such as a lion, even though there is no labeled data for lions.

*One-shot Learning:*One-shot learning deals with scenarios where only a single or a few labeled examples are available for the target activity. The knowledge gained from the source task is used to generalize and make predictions on the target task with limited labeled information.

*Inductive Transfer Learning:*It refers to transferring knowledge from a source area to a target area where the source& target activities are distinct but related.The goal is to leverage the learned representations or features from the source task to improve performance on the target task.

Transductive Transfer Learning: It happens when the source & target activities are the same, but the source & target areas differ.The transfer aims to utilize labeled examples from the source areato enhanceconductance on the target area.

*Unsupervised Transfer Learning:*It contains transferring knowledge from a source area with unlabeled information to a target domain.The focus is on capturing the underlying data distribution and extracting useful features or representations.

*Semi-supervised Transfer Learning:*It mergescomponents of supervised and unsupervised learning.It involves leveraging both labeled information for from the source activity & unlabeled information from the target task to improve performance.

III. LITERATURE SURVEY

Alexander[8] contributed to our understanding of transfer learning for the detection of human activity using sensors. Using weight transfer in our experiment to move models among two sets of data along with sensors from the same dataset. Authors employed PAMAP2 Physical Activity Monitoring dataset & Skoda Mini Checkpoint as the source- and target-datasets. A DeepConvLSTM underpins the network topology that is being used. The outcome of our study demonstrated the need for very differentiated thinking when it comes to transfer learning, as the technique's capacity to provide the intended results is highly dependent on both the architecture as well as the data[8].

Yuxia [9] offers two knowledge graph (KG) based models for explanations of transfer learning that are understandable to people. The first validates the CNN's capacity to transfer characteristics it has learned from a single area to another by pre-training & fine-tuning, while the second describes how zero-shot learning (ZSL) may forecast an example of a target domain using designs from many source domains. Both approaches make use of KG's reasoning power to offer thorough and relatable justifications for the transfer process.

Sizhe [10] suggested a two-part HAR transfer learning paradigm. First, a representational analysis identifies elements that are universally applicable to users and those that are user-specific and require customization. Utilizing this knowledge, we pass the offline classifier's reusable parts to new users and tweak the remaining parts only. Our tests on five datasets demonstrated up to a 43% gain in accuracy & a 66% reduction in training time when contrasted to the baseline without employing TL. Additionally, evaluations on the hardware stage show a 43% & 68% reduction in power &energy usage, accordingly, while maintaining or improving accuracy compared to training from scratch. For consistency, the authors made the source code public.

Jonas et al[11] explore thatwhen a human is involved in the learning process, creates a computational design that allows a robot to learn without the aid of its senses. The authors tested the suggested design in an experimental setting with the humanoid robot iCub in a realistic interactive situation. Without being supervised during the labeling, the human participant interacted in a natural way with the robot exhibiting objects to the iCub. Authors showed that our architecture could be utilized to effectively carry out TL for an object localization system with minimal human supervision & may be examined as a potential improvement of conventional learning techniques for robotics.

Rui Liu [12] To evaluated EmIoT (Emotional Internet of Things) in Mandarin contexts, suggest a multistage DTL approach to develop a high-quality Chinese ETTS (Emotional Text-to-Speech) device within a limited training corpus. This plan transfers to a Mandarin ETTS design the prelearnedknowledge from the earlier steps, which corresponds to high-range neutral English or medium-scale emotional English corpora. Thus, even with a small amount of available emotional corpus, the trained design could produce high-quality emotional speech that may be used for a variety of EmIoT-focused applications. The trials were carried out to show how effective and superior the suggested approach is to its competitors in terms of naturalness and emotional expressiveness.

Yunyuan Gao [13] suggested DSTL (Double Stage Transfer Learning) approach applies TL to both the feature extraction and preprocessing stages of conventional BCIs. The efficacy of the suggested strategy was tested using two open data sets in two different transfer paradigms (MTS and STS). The suggested DSTL outperformed previous state-of-the-art approaches on both sets of data, achieving superior classification accuracy in both cases (84.64% and 77.16% in MTS and 73.38% and 68.58% in STS). The suggested DSTL could decrease target area by offering a novel approach for categorizing EEG data without a training database.

Gjoreski [14] investigated the implications of shifting filters between the data sets, four activity recognition databases were examined. A deep, end-to-end learning architecture was constructed using a spectro-temporal ResNet. In relation to the volume of the target-adaptation information, we examined the number of transmitted CNN residual blocks. The results revealed that tiny adaption subgroups are more effective for transfer learning when there are few diverse activities in the target area. Additionally, the success of the TL scenario appears to be influenced by the resemblance of the domains involved. The most effective transfer had an F1-score of 93%, which is an improvement of 9 % points over a baseline design that was domain-specific.

Xingjian et al [15] introduced DELTA, or DEep Learning Transfer utilizing Feature Map with Attention, a revolutionary regularized transfer learning system. DELTA tries to preserve the source network's outer layer outputs rather than limiting the neural network's weights. DELTA particularly aligns the outcomes of the outermost layers of both systems while minimizing the loss of data by restricting the number of feature maps that have been carefully selected by attention that has been trained through supervision. With the most recent methods, such as L2 and emphL2-SP, authors analyzed DELTA. The findings of the experiment demonstrate that, for new tasks, our technique outperforms these baselines with higher accuracy.

Liu [16] offers a different human-in-the-loop approach that utilizes reinforcement learning that removes the pre-labeling constraint and continuously improves the model as more data is gathered. The objective is to maximize Re-ID (Re-identification) performance while minimizing human annotation efforts. Through adjusting the RL strategy and CNN variables alternatively, it operates in an iteratively updating context. In order to help anparticipant (a design in a RL method) choose training instances instantly by a human user, we develop the DRAL approach. Extensive studies show that our DRAL approach for human-in-the-loop person Re-ID using DRL is superior to existing unsupervised &transfer learning designs & active learning designs.

Liang Zhao [17] Utilizing co-occurrence information, suggest a deep semantic mapping approach to DHTL (Deep semantic mapping model for Heterogeneous multimedia Transfer Learning). In particular, authors combined DNN with CCA to create a deep correlation subspace that serves as the joint semantic specification for connecting information from various areas. The recommended DHTL constructs a multi-layer correlation matching system spanning areas, with the CCA connecting every pair of hidden domain-specific levels. A shared objective feature is established, & the optimization methods are described, in order to train the network. The shared properties of the source area are transmitted for task learning in the target areaonce the deep semantic representation has been obtained.Numerous tests with three different multimedia identification apps show that the suggested DHTL is better to other state-of-the-art deep TL approaches in its ability to select deep semantic representations for diverse domains. Table 1 evaluates the available work in tabular form to better comprehend the various transfer learning strategies in human-like computing:

Table 1. Tabular Form of Existing Papers

Sizhe[10]	HAR TL architectures with 2 elements.		five datasets	43% accuracy enhancement&66% training time reduction
Gjoreski [14]	Spectro-temporal ResNet was implemented	CNN	four activity recognition datasets	F1-score of 93%
Rui Liu [12]	To designed a high-quality Chinese ETTS device.	Multistage deep transfer learning scheme	A significant corpus of neutral English & a medium-sized corpus of emotive English	Experiments showed that the suggested approach was stronger as well as better to alternatives in the areas of simplicity or conveying feelings.
Xingjian [15]	a brand-new regularize TL architecture called DELTA that keeps the source network's outer layer responses.	State-of-the-art approaches, containing L2 &\emphL2-SP	-	The findings of the study demonstrate that, for novel assignments, our technique surpasses these baselines with greater precision..
Liang Zhao [17]	Proposed a deep semantic mapping design for DHTL.	DNN with CCA	co-occurrence data	Numerous tests with three different multimedia recognition apps show that the suggested DHTL is better to other state-of-the-art deep TL approaches in its ability to identify deep semantic models for diverse fields.
Yunyuan Gao [13]	It was suggested that the preprocessing stage as well as the feature extraction phase should be standard BCIs.	DSTL approach	two public datasets MTS and STS	The proposed DSTL outperformed previous SOA approaches on two databases, achieving superior classification accuracy in both cases (84.64% & 77.16% in MTS and 73.38% & 68.58% in STS).
Jonas [11]	Analytical that enables a robot to get knowledge from its sensors on its own.	Transfer learning	iCub	Accomplished TL for an object localization system with minimal human supervision, which may be viewed as a potential improvement to the standard robotics learning techniques.

IV. TRANSFER LEARNING IN HUMAN-LIKE COMPUTING

Transfer learning plays a crucial part in advancing the field of human-like computing by enabling machines to acquire and apply knowledge in a manner that resembles human learning and cognition. Following are some key reasons why transfer learning is important in the development of human-like computing [18]:

Mimicking human learning: Humans excel at transferring knowledge and skills acquired from one domain to another. Transfer learning allows machines to mimic this ability through leveraging knowledge gained from one domain & applying it to another. By enabling machines to transfer learned representations, human-like computing systems can exhibit similar capabilities, adaptability, and flexibility.

Overcoming data limitations: One major challenge in human-like computing is the scarcity of labeled training data for specific tasks. Transfer learning mitigates this challenge by utilizing pre-trained models that have learned representations from large and diverse datasets. By transferring this knowledge to new tasks with limited data, human-like computing systems can effectively learn from smaller datasets, enabling them to generalize better and perform well even in data-limited scenarios.

Faster learning and convergence: Training deep learning models from scratch can be computationally intensive and time-consuming. Transfer learning accelerates the learning process by starting with pre-trained models that have already learned meaningful representations. This initialization speeds up convergence, reduces training time, and allows human-like computing systems to learn faster.

Generalization across tasks: Human-like computing systems need to be capable of understanding and performing a wide range of tasks. Transfer learning facilitates better generalization by transferring knowledge across related or unrelated tasks. By capturing and transferring underlying patterns, representations, and concepts, transfer learning enables machines to apply their learned knowledge to new tasks, exhibiting a higher level of adaptability and versatility.

Problem-solving: Transfer learning is essential in modeling complex cognitive processes and problem-solving abilities in human-like computing systems. By emulating how users leverage prior knowledge to solve new problems, transfer learning enables machines to reason, infer, and solve problems in a more human-like manner. This opens up possibilities for applications such as natural language understanding, decision-making, and creative problem-solving.

Advancing human-AI collaboration: In an era where human-AI collaboration is becoming increasingly important, transfer learning can facilitate seamless integration between humans and machines. By leveraging the learned knowledge and representations, human-like computing systems can complement human expertise, enhance decision-making, and provide valuable insights in various domains, ranging from healthcare and finance to education and entertainment.

A. Techniques

TL approaches have been widely adopted in the area of human-like computing, where the goal is to develop AI systems that can mimic human cognitive abilities. This could beaccomplish by fine-tuning the pre-trained design, extracting features from the pre-trained design, or adapting the pre-trained design to the new task [19].

*Fine-tuning:*Fine-tuning is a transfer learning technique commonly employed in human-like computing. It involves taking a pre-trained design, typically learned on a large-scale database, & adapting it to a specific task or domain related to human cognition. The initial layers of the pre-trained model are kept intact, and only the final layers are replaced or modified to suit the target task. Fine-tuning allows the model to retain its general understanding of human-like features while adapting to specific cognitive tasks.

*Feature Extraction:*Feature extraction is another transfer learning technique used in human-like computing. In this approach, pre-trained models are employed as feature extractors. The lower layers of the model, which capture low-level features like edges and textures, are used as a fixed feature extractor. The removed properties are then fed into a new design, which is learned specifically for the target cognitive task. By leveraging pre-trained models as feature extractors, human-like computing models can benefit from the learned representations while focusing on task-specific learning.

Model Adaptation: Model adaptation involves modifying an existing cognitive model to adapt it to a different but related cognitive task. This technique is particularly useful when the target task shares similarities with the source task, allowing for the transfer of learned representations. Model adaptation may involve adjusting the model architecture, incorporating new modules or layers, or fine-tuning specific components to optimize performance for the target task. By adapting an existing model, the computational and time costs associated with training a new model from scratch can be significantly reduced.

To better understand the different transfer learning techniques in human-like computing, table 2 compares the three kinds of TL:

Table 2. Comparison of TL Techniques

Type	Specification	Advantages	Disadvantages
Fine Tuning	The weights of the pre-trained model are updated using the training data for the new task.	Attain good performance with a less set of training information.	Time-consuming and computationally expensive.
Feature extraction	In order to obtain characteristics from the input information, a model that has been trained is utilized. A fresh model is then trained using these characteristics for the intended job.	Can be used with a different model architecture than the pre-trained design.	Less accurate than fine-tuning.
Model Adaptation	The pre-trained design is modified to be more suitable for the target task.	Attains better performance than fine-tuning or feature extraction.	In terms of analysis, it is more costly and time-consuming.

B. Applications

Transfer learning techniques have found numerous applications in the field of human-like computing, enabling AI systems to simulate and replicate various aspects of human cognition [20]. Figure 1 shows some notable applications:

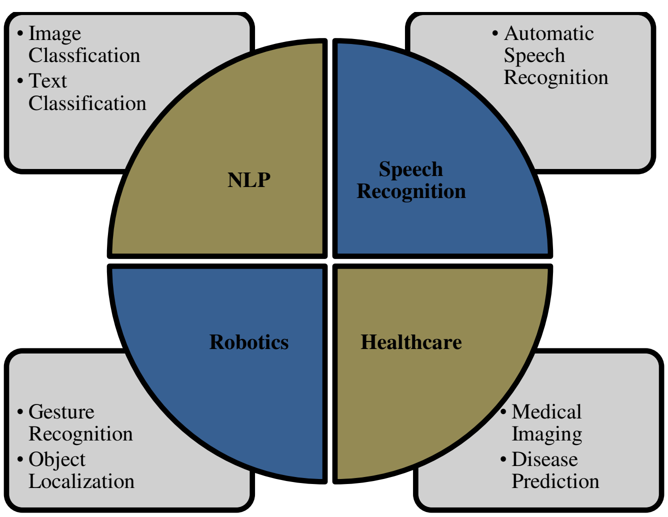

Fig. 1. Applications of Transfer Learning

Computer Vision

1) Image Classification: Transfer learning is extensively used for image classification tasks, such as identifying objects, animals, or scenes in images.

2) Object Detection: It helps improve the accuracy and speed of object detection systems, enabling them to locate and identify objects in images or videos.

3) Semantic Segmentation: Transfer learning aids in segmenting images into meaningful regions, allowing for detailed understanding and analysis of visual data.

4) Facial Recognition: Transfer learning is applied to recognize and verify individuals' faces in applications like security systems or social media platforms.

Natural Language Processing (NLP)

1) Sentiment Analysis: Transfer learning assists in determining the sentiment or emotion expressed in character, enabling applications like sentiment analysis in social media or customer feedback analysis.

2) Text Classification: It aids in categorizing text into predefined classes or topics, such as news classification or spam detection.

3) Named Entity Recognition: Transfer learning is utilized to identify and extract named entities like names, organizations, or locations from text.

4) Machine Translation: Transfer learning helps improve the accuracy and fluency of machine translation systems by leveraging pre-trained language models.

*5) Image Classification:*TL could be used to enhance the conductance of image classification models. For instance, a pre-trained design can be used to removeproperties from pictures, &then these characteristics can be used to educate a new design for a particular activity, such as classifying images of plants and animals.

Speech Recognition:

TL could be used to enhance the conductance of speech recognition models. For instance, a pre-trained design can be used to remove properties from audio, & then these properties can be used to learn a new design for a particular activity, such as transcribing speech or identifying speakers.

1) Automatic Speech Recognition (ASR): Transfer learning is employed to enhance the accuracy of ASR systems, enabling accurate transcription of spoken language into text.

2) Speaker Identification: It helps identify or verify individuals based on their unique voice characteristics, facilitating applications like voice authentication or speaker idolization.

Healthcare

1) Medical Imaging: Transfer learning assists in diagnosing and classifying medical images, such as X-rays or MRIs, aiding in early detection of diseases or abnormalities.

2) Disease Prediction: It enables the prediction and prognosis of various medical conditions based on patient data, contributing to personalized medicine and treatment planning.

Robotics and Autonomous Systems

1) Object Recognition and Localization: Transfer learning carry robots and autonomous systems in recognizing and localizing objects in their environment, enabling efficient navigation and interaction [21].

2) Gesture Recognition: It helps robots understand and interpret human gestures, facilitating human-robot interaction and collaboration.

Here are some additional examples of how transfer learning is being used in human-like computing:

Stock Market Prediction: Transfer learning is used to analyze historical stock data and make predictions on future market trends, aiding in decision-making for traders and investors.

Virtual assistants: Virtual assistants like Amazon Alexa use transfer learning to understand natural language commands [22].

Self-driving cars: Self-driving cars use transfer learning to identify objects on the road, such as cars, pedestrians, and traffic signs.

*Robotics:*TL is being utilized to create robots which can pick up skills from watching people execute activities.

In short, TL approaches have a huge range of apps in human-like computing, consisting NLP, computer vision, emotion recognition, speech processing, &cognitive reasoning. By utilizing pre-existing knowledge and representations, AI systems can effectively understand and respond to human-like behaviors, enabling them to simulate different aspects of human cognition and interaction. These applications hold promise for the development of more intelligent and empathetic AI systems that can assist humans across various tasks and domains.

V. RESEARCH GAPS

Based on the literature survey, the following research gaps can be identified in the context of transfer learning for human-like computing:

- The existing transfer learning methods are often sensitive to the similarity between the source and target domains. This can be a problem in real-world applications, where the target domain may be significantly different from the source domain. More robust and generalizable transfer learning methods are needed to address this challenge.
- The existing transfer learning methods can be computationally expensive, especially when the source domain is large. More efficient transfer learning methods are needed to make them more practical for real-world applications.
- The majority of the research on transfer learning has been focused on computer vision and natural language processing tasks. More research is needed on transfer learning for other application domains, such as healthcare, robotics, and finance.
- In many real-world applications, data from different modalities, such as audio, video, and text, needs to be combined for transfer learning. However, there are many challenges associated with transfer learning in cross-modal settings. More research is needed to address these challenges.
- Integrating human-centric factors comprehensively into transfer learning models requires exploration. Incorporating user preferences, cognitive feedback, and intuitive interactions could lead to AI systems aligned with human expectations.
- Adjusting transfer learning approaches based on changing data distributions requires investigation. Developing methods for AI systems to autonomously detect shifts and adapt strategies could maintain performance over time.

VI. CONCLUSION AND FUTURE SCOPE

This review paper has discussed transfer learning in human-like computing, focusing on its applications and challenges. Various techniques such as fine-tuning, feature extraction, and model adaptation in domains like NLP, computer vision, emotion recognition, speech processing, and cognitive reasoning have also been explored. By leveraging pre-trained models, AI systems can better understand human-like behaviors. However, challenges exist, and ongoing research is needed to develop more effective transfer learning techniques in this field.

Future Scope

The field of transfer learning in human-like computing holds tremendous potential for further advancements. The following areas provide promising avenues for future research:

- Domain Adaptation Techniques
- Task-Specific Transfer Learning
- Data-Efficient Transfer Learning
- Fairness and Ethical Considerations

In conclusion, transfer learning techniques have shown immense promise in advancing human-like computing. Transfer learning paves the way for machines to bridge the gap between artificial intelligence and human intelligence, leading to more capable and intelligent human-like computing systems.By addressing the existing challenges and exploring the future research directions outlined above, one can pave the way for more sophisticated, adaptable, and ethical AI systems that closely simulate human cognition and enhance human-machine interactions in a wide range of applications.

REFERENCES

[1] L. A. Torrey and J. W. Shavlik.: Chapter 11 Transfer Learning. Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques, IGI Global(2009).

[2] R. E. Haskell.: Transfer of Learning: What It Is and Why It's Important. Proceedings of the IEEE International Conference on Advanced Learning Technologies(2001).

[3] F. Zhuang, Z. Qi, K. Duan, D. Xi, Y. Zhu, H. Zhu, H. Xiong, and Q. He.: A Comprehensive Survey on Transfer Learning. Proceedings of the IEEE, Vol. 109, pp. 43-76 (2019).

[4] P. D. Alfano, V. P. Pastore, L. Rosasco, and F. Odone.: Fine-tuning or top-tuning? Transfer learning with pretrained features and fast kernel methods. arXiv, abs/2209.07932(2022).

[5] J. Yang, G. Xiao, Y. Shen, W. Jiang, X. Hu, Y. Zhang, and J. Peng.: A Survey of Knowledge Enhanced Pre-trained Models. arXiv, abs/2110.00269 (2021).

[6] J. Lu, V. Behbood, P. Hao, H. Zuo, S. Xue, and G. Zhang.: Transfer learning using computational intelligence: A survey. Knowledge-Based Systems, vol. 80, pp. 14-23 (2015).

[7] K. R. Weiss, T. M. Khoshgoftaar, and D. Wang.: Transfer Learning Techniques. Big Data Technologies and Applications, pp. 53-99 (2016).

[8]Alexander Hoelzemann,Kristof Van Laerhoven.: Digging deeper: towards a better understanding of transfer learning for human activity recognition. ISWC '20: Proceedings of the 2020 ACM International Symposium on Wearable Computers, pp. 50–54(2020).

[9] YuxiaGeng, Jiaoyan Chen, Huajun Chen.: Human-centric Transfer Learning Explanation via Knowledge Graph [Extended Abstract](2019).

[10] SizheAn,GanapatiBhat,SuatGumussoy,UmitOgras.: Transfer Learning for Human Activity Recognition Using Representational Analysis of Neural Networks. ACM Transactions on Computing for Healthcare, 4(1), pp 1–21 (2023).

[11] Jonas Gonzalez-Billandon, Alessandra Sciutti2, Giulio Sandini1 , Francesco Rea.: Towards a cognitive architecture for self-supervised transfer learning for objects detection with a Humanoid Robot. IEEE(2021).

[12] Rui Liu; Qi Liu; Hongxu Zhu; Hui Cao.: Multistage Deep Transfer Learning for EmIoT-Enabled Human–Computer Interaction. IEEE Internet of Things Journal 9(16)(2022).

[13] Yunyuan Gao, Mengting Li, Yun Peng, Feng Fang, Yingchun Z.: Double Stage Transfer Learning for Brain–Computer Interfaces. IEEE Transactions on Neural Systems and Rehabilitation Engineering ,Vol 31(2023).

[14]Gjoreski, M., Kalabakov, S., Luštrek, M., &Gjoreski, H.: Cross-dataset deep transfer learning for activity recognition.Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers - UbiComp/ISWC ’19(2019).

[15]Xingjian Li, HaoyiXiong,ZeyuChen,JunHuan,Ji Liu.: Knowledge Distillation with Attention for Deep Transfer Learning of Convolutional Networks. ACM Transactions on Knowledge Discovery from Data, 16(3)(2021).

[16] Liu, Z., Wang, J., Gong, S., Tao, D., & Lu, H,: Deep Reinforcement Active Learning for Human-in-the-Loop Person Re-Identification. IEEE/CVF International Conference on Computer Vision (ICCV)(2019).

[17]Liang Zhao, ZhikuiChen,Laurence T. Yang,M. Jamal Deen.: Deep Semantic Mapping for Heterogeneous Multimedia Transfer Learning Using Co-Occurrence Data. ACM Transactions on Multimedia Computing, Communications, and Applications, 15(9), pp 1–21(2019).

[18] J. Lu, V. Behbood, P. Hao, H. Zuo, S. Xue, and G. Zhang.:Transfer learning using computational intelligence: A survey. Knowledge-Based Systems, vol. 80, pp. 14-23(2015).

[19] M. E. Peters, S. Ruder, and N. A. Smith.: To Tune or Not to Tune? Adapting Pretrained Representations to Diverse Tasks. arXiv, abs/1903.05987(2019).

[20] Y. Liu.: A Review About Transfer Learning Methods and Applications. Proceedings of the IEEE International Conference on Data Mining (2011).

[21] R. Saeedi, H. Ghasemzadeh, and A. H. Gebremedhin.: Transfer learning algorithms for autonomous reconfiguration of wearable systems. IEEE International Conference on Big Data (Big Data), pp. 563-569(2016).

[22] M. Ranaweera and Q. H. Mahmoud.: Virtual to Real-World Transfer Learning: A Systematic Review. Electronics, 10(12), pp. 1959, (2021).