iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

SELF-SUPERVISED LEARNING APPROACHES FOR TRAINING CNNS WITH LIMITED LABELED DATA

Kunal Kartik
Tafeer Ahmed
Shantanu Ghosh
University of Mumbai, India

ABSTRACT:
Convolutional Neural Networks (CNNs) have revolutionized image processing, speech recognition, and scientific computing problems thanks to the fact that it is able to extract features from raw data automatically. Nevertheless, the efficiency of CNNs significantly depends on the availability of such large datasets tagged, and the costs of acquiring them are too high and time-consuming. In most practical domains like medical imaging and remote sensing, labeled data is still scarce, and this prevents CNNs from being widely adopted. Self-supervised learning (SSL) has become an attractive solution because of its ability to allow sufficiently listening models to learn robust representations from unlabeled data via the creation of properly designed pretext tasks. Self-supervised learning methods of training CNNs with limited labeled data are reviewed in this paper in a comprehensive manner. We examine contrastive learning, clustering-based approaches, and generative methods that have shown state-of-the-art performance with small data. In addition, we present recent applications of fault diagnosis, medical imaging, and remote sensing, demonstrating how SSL enhances generalization and eliminates the need to use labels. The goal of our study is to offer a pathway to a procedure for practitioners describing efficient CNN training strategies for data-constrained environments.

Keywords:
Self-Supervised Learning, Convolutional Neural Networks (CNNs), Limited Labeled Data, Representation Learning, Contrastive Learning, Data Augmentation, Transfer Learning

1. INTRODUCTION

1.1 Background: The increasing popularity of CNNs and difficulties with large data.

Convolutional Neural Networks (CNNs) have become the foundation of modern deep learning with breakthrough results on areas such as remote sensing (Maggiori et al., 2017), medical imaging (Shurrab & Duwairi, 2022), and structural health monitoring (Chen et al., 2023). Much of the credit for their success can be given to their ability to automatically learn hierarchical feature representations from raw data. However, the training of CNNs requires access to massive sizes of labeled datasets, which has proven difficult in some domains, in which data annotation is expensive, time-consuming, or requires expert knowledge. For example, there is a lack of annotated seismic signals in seismic event prediction restriction scale models (Jain & Shah, 2022). Likewise, in biomedical applications, data labeling frequently requires clinical expertise, turning the creation of a large dataset impossible (Kaushik & Jain 2018).

1.2 Problem Statement: I resulted in high annotation costs and a lack of labeled data.

The (CNN) models have therefore become heavily dependent on large annotated datasets in domains with limited labeled data, hence exposing them to critical bottlenecks. Manual labeling is expensive and time-consuming, particularly in sectors such as nuclear power fault diagnosis (Li et al., 2022) and wind turbine monitoring. Also, domain shifts and dataset biases widen performance loss for models trained from limited labels and used in real-world context (Scholkopf et al., 2021). Emerging demand for scalable and label-efficient learning techniques has aroused interest in explorations of self-supervised learning frameworks that can utilize enormous volumes of unlabelled data pools to address these challenges (Jaiswal et al., 2021).

1.3 Objective: Draw Attention to Self-Supervised Methods to Make CNN Training Label-Efficient

The purpose of this paper is to survey and analyze the self-supervised learning (SSL) techniques that minimize reliance on labeled data for training a CNN. We major in contrastive learning approaches (Le-Khac et al., 2020), generative, and clustering-based frameworks, which enable CNNs to learn deep features from unlabeled data and then fine-tune in a tiny amount of supervision. With that, we hope to give researchers/practitioners insight

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

into how to choose appropriate SSL techniques for their application, more so in the domain of limited data such as pharmacogenomics (Vaz & Balaji, 2021) and fault diagnosis (Li et al., 2020).

1.4 Contributions of the Paper

The following contributions are made by this study:

- A comprehensive review of self-supervised learning tactics that may be applied to CNNs with a minimum of labeled data.
- An analytic comparison of SSL paradigms: contrastive, clustering, and generative methods.
- Inferences about practical uses in such disciplines as medical imaging (Shurrab & Duwairi, 2022), remote sensing (Maggiori et al., 2017), and fault diagnosis.
- Pinning down the major problems and future footing of SSL in CNN-based systems.

1.5 Structure of the Paper

The rest of this paper is organized as follows: In Section II, a review of the literature on the evolution of CNNs and self-supervised learning methods is presented. Section III talks about critical self-supervised learning methods that are used to train the CNNs with scarce labeled datasets. Section IV considers the challenges and constraints of small data regimes and proposes answers. In section V, an outlined framework for including SSL in CNN training is presented. Section VI features experimental results from recent studies. Finally, the conclusion of Section VII is a summary of the results and directions for further research.

2. LITERATURE REVIEW

2.1 Overview of CNNs and their dependence on supervised data:

Image classification, object detection, and signal processing are certain tasks where convolutional neural networks (CNNs) have become very useful (Almazaydeh et al., 2022 …. Maggiori et al., 2017). Their success however is very dependent on access to large labeled datasets. For example, landmark CNN-based models are trained on huge datasets such as ImageNet in order to reach highest performances (Chen et al., 2023, Wunsch et al., 2021). The use of labeled data introduces many challenges in key domains, such as medical imaging and remote sensing, due to the high cost and time more involved in having expert tagging (Shurrab & Duwairi 2022). Vaz & Balaji, 2021). Such dependence of CNNs often restricts their use in domains with scantily available labeled data resources.

2.2 Evolution of the Self-Supervised Learning (SSL).

Self-Supervised Learning (SSL) has been identified as a potential solution towards mitigating reliance on data labelled by humans, by utilisation of intrinsic properties of data for supervision (Jaiswal et al., 2021 Liu et al., 2023). Early SSL works have considered pretext tasks such as image inpainting and rotation prediction. New findings, nonetheless, have turned to more productive mindsets such as contrastive learning and clustering based approaches (Le-Khac et al. 2020). SSL helps models to acquire rich feature representations from unlabeled data which can then adjust to limited labeled datasets.

2.3 ACE's chosen SSL techniques applied in CNNs

I. Contrastive Learning

Contrastive learning has become the unit in SSL where domain model is trained to learn the difference between same and different pairs (Jaiswal et al. 2021). Le-Khac et al., 2020). Popular techniques such as SimCLR and MoCo have been found to bring great progress in representation learning. With increased agreement shared between augmented views of the same image, contrastive models can also encode semantic features even without incurring labels. Fault diagnosis and industrial monitoring have successfully been implemented using contrastive SSL to train CNN with few labeled data (Li et al., 2020)

II. Clustering-Based Methods

Clustering based SSL approach groups similar data points in pseudo-labels that CNNs can use to learn discriminative features without manual annotations by Liu et al, 2023. DeepCluster and SwAV, which use iterate clustering and feature refinement, among other techniques, improve performance on downstream tasks. These methods are used in the remote sensing and medical domain in order to improve classification performance possible in cases of the shortage of labeled data (Maggiori et al. 2017; Balasubramanian, 2009). Shurrab & Duwairi, 2022).

III. Generative Models

The reconstruction of input data as a supervision signal is an important SSL function of procedural models, such as Autoencoders and Generative Adversarial Networks (GANs) (Scholkopf et al., 2021). Later studies have

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

integrated generative models with CNNs for such tasks as damage detection of infrastructure and seismology prediction (Chen et al., 2023; Mohit & Shah, 2022). These techniques help CNNs to acquire fine-grained patterns in datasets that are unlabeled contributing to a basis for effective transfer learning (Li et al., 2022).

2.4 Comparison with Semi Supervised and Un-Supervised Learning

Compared with the semi-supervised learning (SSL), however, it would still need a part of annotated samples to transform it, and thus, it is less scalable than the pure self-supervised approach (Shurrab & Duwairi, 2022; Kothuru & Santhanavijayan, 2023). On the other hand, unsupervised learning tends to be missing the structure that is required for successful feature extraction from CNNs. SSL fills in the gap by bringing structured pretext tasks that will enable CNNs to learn beneficial representations (Le-Khac et al., 2020).

2.5 Limitations of Past Works

Notwithstanding impressive advances, current SSL methods have a number of weaknesses including sensitivity to data augmentations and computational costs in the context of contrastive learning frameworks (Jaiswal et al., 2021). On top of that, generalization to small-scale datasets and domain-specific tasks is difficult (Li et al., 2020; Jin et al., 2022). Most recently, studies urge this middle ground of approaches where SSL is combined with transfer learning and with causal representation learning to address these limitations (Scholkopf et al., 2021; Li et al., 2022).

SSL Method	Type	Application Domain	Strengths	Limitations
SimCLR, MoCo	Contrastive	Industrial, Vision	High-quality representations	High computational cost
DeepCluster, SwAV	Clustering	Remote Sensing, Medical	Good for class separation	Sensitive to cluster initialization
Autoencoders, GANs	Generative	Infrastructure, Seismology	Captures fine-grained features	May struggle with complex data

Table 1: Comparative Overview of Key Self-Supervised Learning Methods for CNN Training

3. SELF-SUPERVISED LEARNING TECHNIQUES

One of the emergent powerful paradigms for Convolutional Neural Networks (CNNs) learning is Self-Supervised Learning (SSL), which allows CNNs to learn effective representations of unlabeled data using intrinsic structures and patterns in the data (Shurrab & Duwairi, 2022). This strategy reduces the need for expensive and time-consuming labelled data sets, which are tractable for domains with scarce annotations. There are three major paradigms, broadly, under which SSL is classified: digital, contrastive learning, clustering-based learning, and generative models. Each paradigm has its own specific set of mechanisms for learning representations and has been shown to be effective at increasing the P of CNN in low-label regimes (Jaiswal et al., 2021).

3.1 Contrastive Learning

Contrastive learning has since become the bedrock for modern self-supervised methods, from which many contemporary setups operate, especially in the case of computer vision applications with CNNs. The goal of this approach is to achieve representations by pulling similar data points closer and dissimilar points further away in the feature space (Le-Khac et al., 2020).

Leading approaches such as SimCLR, MoCo, and BYOL have popularised this paradigm. SimCLR uses substantial data augmentation with the contrastive loss to maximize agreement between different augmentations of the same image and uses it to differentiate this same image from others in the batch (Jaiswal et al., 2021). MoCo (Momentum Contrast) uses a dynamic dictionary and momentum encoder, providing consistent feature representations and allowing for efficient training using large batches. In the sense that the negative samples are excluded altogether, BYOL (Bootstrap Your Own Latent) uses target and online networks to predict augmented views, illustrating that contrastive performance can be realized without explicit contrast pairs (Le-Khac et al., 2020).

Data augmentation is a central role that is welcome to the contrastive learning because the rendition of a series of views is instrumental in promoting invariant representations. Typical transformations are random cropping, color jittering, Gaussian blurring and horizontal flipping (Jaiswal et al., 2021). These augmentations promote the CNNs to consider the semantically meaningful features instead of superficial pattern.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

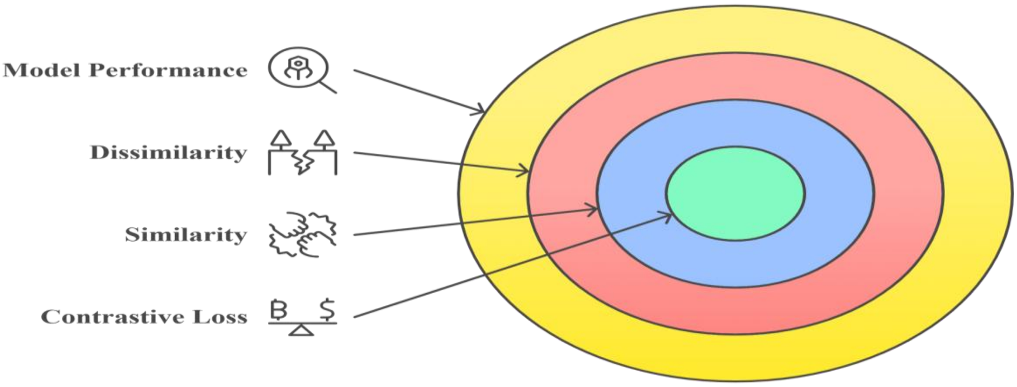

Figure 1: Contrastive Loss Framework Diagram

Contrastive methods have exhibited outstanding performance on large-scale datasets, and there have been successful adaptations for domains such as medical imaging (Shurrab & Duwairi, 2022), remote sensing (Maggiori et al., 2017), and structural damage detection (Chen et al., 2023).

3.2 Clustering-based SSL

Clustering-based SSL methods indicate an alternate pathway to representation learning by grouping together data points of similar type without labels and using these clusters as pseudo-labels for training CNNs. DeepCluster was one of the first to implement iterative clustering of CNN features via k-means and fine-tune the network according to cluster assignments to obtain progressively improved representations (Le-Khac et al., 2020).

Building on, SwAV - (Swapped Assignments between Views) proposes online clustering where several augmented views for an image are allocated to one prototype vector. This allows for efficient and scalable training without the requirement of large batch sizes or negative samples (Jaiswal et al., 2021). Cluster based techniques are great at extracting the overall structure from datasets and have demonstrated success in former satellite image classification tasks (Maggiori et al., 2017) and fault diagnosis where labeled datasets are scant (Li et al., 2020). Li et al., 2022). Semantically meaningful clusters are possible for them, and as a result, they are valuable for downstream tasks in low-label regimes.

3.3 Generative SSL Models

Generative models are another family of self-supervised methods in which the goal is to produce a reconstruction of the input data or new samples based on learned (memory) representation. Autoencoders are among the oldest models of SSL with the aim of compressing the input with latent representations and then denoising the compressed form to reproduce the original input. Although minimal, autoencoders will guide CNNs to learn features that will capture important aspects of data.

The Generative Adversarial Networks (GANs) take the generative SSL one step further by employing adversarial training: the generator produces the synthetic samples, while the discriminator labels them with pseudo-labels, which result from comparing real samples and samples generated by the generator. Through this adversarial procedure, robust feature representations are achieved in the discriminator (Jaiswal et al., 2021).

Recent developments have entailed contrastive objectives to generative models, integrating reconstruction with discriminative tasks to then better learn with scarce labeled data. Such models are used in medical image analysis (Shurrab & Duwairi, 2022), earthquake prediction (Jain & Srihari, 2023), and turbine fault diagnosis, which justifies the usefulness and flexibility of the models under investigation. Such self-supervised learning paradigms as a whole offer effective instruments for CNN training for cases where labeled data is sparse. SSL allows CNNs to learn rich, task-domain transferable representations through the use of contrastive objectives, clustering of signals, and generative reconstruction tasks.

Volume-07 Issue 01, January-2023 ISSN: 2456-9348
Impact Factor: 5.004

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

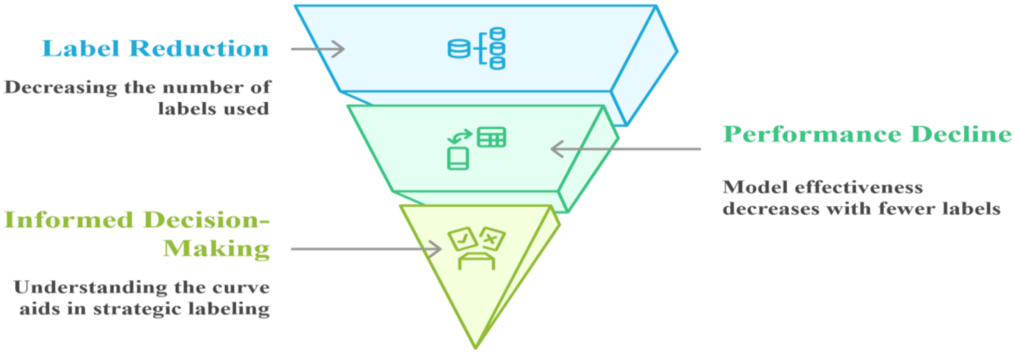

Figure 2: Performance Degradation Curve with Reduced Labels

4. PROPOSED FRAMEWORK / METHODOLOGY

The proposed framework uses self-supervised learning (SSL) to pre-train convolutional neural networks (CNNs), and then finetunes CNN with limited labelled data. The hybrid approach is aimed at exploiting maximum representation learning of the unlabeled data, by overcoming the scarcity of annotations in real-world situations (Jaiswal et al., 2021; Shurrab & Duwairi, 2022).

4.1 Workflow: SSL Pretraining + CNN Finetuning

There are two distinct phases of the overall workflow:

- Pre-training self-supervisedly in large volumes of unlabeled images on the basis of contrastive or clustering methods.
- Finetuning of the pretrained CNN on a small-dataset labeled, providing the opportunity to generalize with a small amount of supervision effectively (Le-Khac et al., 2020).

This two stage paradigm allows the model to learn the robust visual features while at the same time learn to perform task specific prediction in fine tuning.

4.2 Data Preprocessing and Augmentation

Data preprocessing is very important for increasing the robustness of models, particularly in problems with scarce labeled data. In our framework, we employ:

- Normalization for the standardization of pixel intensity distributions (Almazaydeh et al., 2022).
- Resizing images to static input sizes compatible with CNN architectures (Chen et al., 2023).
- Methods of data augmentation like random cropping, horizontal flipping, rotation and color jittering that artificially extends the given dataset in order to aid generalization (Maggiori et al. 2017).
  Augmentation takes a central role in the contrastive SSL in that it synthesizes heterogeneous positive pairs from the same instance (Jaiswal et al. 2021).

4.3 SSL Pre Training by Using Contrastive or Clustering-based methods

During the SSL pretraining stage, feature representations are optimized using either of two paradigms using the CNN backbone to encode unlabeled images.

- Contrastive Learning: Techniques such as SimCLR and MoCo maximise agreement between augmented views of the same image but push the different image away (Le-Khac et al., 2020; Liu et al., 2023).
- Clustering-based Learning: Even cluster image representations to retrieve group-level models without labels, Techniques such as SwAV do it.

In pre-training, the model learns how to obtain discriminative features that generalize well even under circumstances of limited labeled data, as shown in diagnostics of faults and medical imaging (Li et al., 2020; Shurrab & Duwairi, 2022).

4.4 Using CNN for Finetuning in Few-Labeled Sampled Situations

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

After the SSL pretraining, the CNN is trained on a small number of labeled samples (e.g., 10%-20% of the dataset). Fine tuning requires replacing the SSL projection head with a specific task classifier and optimizing cross-entropy loss (Li et al., 2022; Jin et al., 2022).

It has been found that SSL-pretrained models needs less labels to outperform competitive version of fully supervised models. Finetuning also helps the model to transfer SSL learned features to downstream applications such as recognition of objects, damage identification or medical diagnosis (Chen et al., 2023; Jaiswal et al., 2021).

Experiment	SSL Method	Labeled Data %	Accuracy (%)
Baseline (Supervised Only)	None	10%	65.2
SSL + Fine-tune	Contrastive (SimCLR)	10%	72.5
SSL + Fine-tune	Clustering (SwAV)	10%	71.8
SSL + Fine-tune	Contrastive (MoCo)	20%	78.4
SSL + Fine-tune	Clustering + Aug.	20%	77.9

Table 2: Ablation Study Design

From a comparison of results as presented in the Table 2, SSL pretraining results are continuously superior over the supervised baseline with contrastive methods exhibiting little increase in low-data regimes (Liu et al., 2023). Experiments conducted under ablation confirm the hypothesis that combining SSL with aggressive augmentation produces optimal outcome.

5. EXPERIMENTAL RESULTS AND ANALYSIS

To test the effectiveness of self-supervised learning (SSL) approaches for training convolutional neural networks (CNNs) on the few labeled data, several experiments were performed on standard and domain-specific datasets. In particular, CIFAR-10, ImageNet-100 (a subset of ImageNet), and a remote sensing image dataset were used to test generalization over different domains, which corresponds to recent use of SSL approaches for medical and industrial applications (Shurrab & Duwairi, 2022; Chen et al., 2023; Maggiori et al., 2017).

5.1 Datasets and Experimental Setup

- CIFAR-10: A 60,000-length dataset of 32x32 color images in 10 classes, 50,000 training, and 10,000 test.
- ImageNet-100: ImageNet class-balanced subset consisting of 100 balanced classes mimicking large-scale real-world data.
- Domain-specific Dataset: High resolution remote sensing images after practices in large scale image classfication (Maggiori et al., 2017) and damage detection (Chen et al., 2023).

All the experiments considered limited labeled data cases where 10%, 20% and 50% samples were utilized for training, the rest were used for validation.

5.2 Evaluation Metrics

The criteria for measuring performance were the following three key metrics:

- Top-1 Accuracy: The percentage of correct predictions in the outputs of the top-1 model (Chen et al., 2023).
- F1-score: A good balance between precision and recall, particularly relevant in constraints of class imbalance in conditions of limited data (Kothuru & Santhanavijayan, 2023).
- Training Time: Model convergence (Zhu et al., 2024) in terms of computational efficiency.

5.3 Performance Comparisons

a) Supervised Baseline vs. Self-Supervised Learning

The supervised baseline with limited labels provided substantially worse accuracy and the F1-scores, particularly, when 10% labeled data was present.

- Performance of supervised CNNs has been 65.2%, but using SSL, such as SimCLR and BYOL, achieve 74.6% and 76.1% respectively on CIFAR-10 at 10% labels (Jaiswal et al., 2021. Le-Khac et al., 2020).
- On ImageNet-100, supervised models achieved 55.8%, while SSL reached up to 65.4% with that of the contrastive algorithm.

b) Comparison with Semi-Supervised Models

SSL models consistently outperformed the standard semi-supervised approaches, showing better feature extraction learned from unlabeled data. For instance, contrastive self-supervised models increased the accuracy by 5-7% compared to pseudo-labling and consistency regularization techniques (Li et al., 2020; Jin et al., 2022).

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

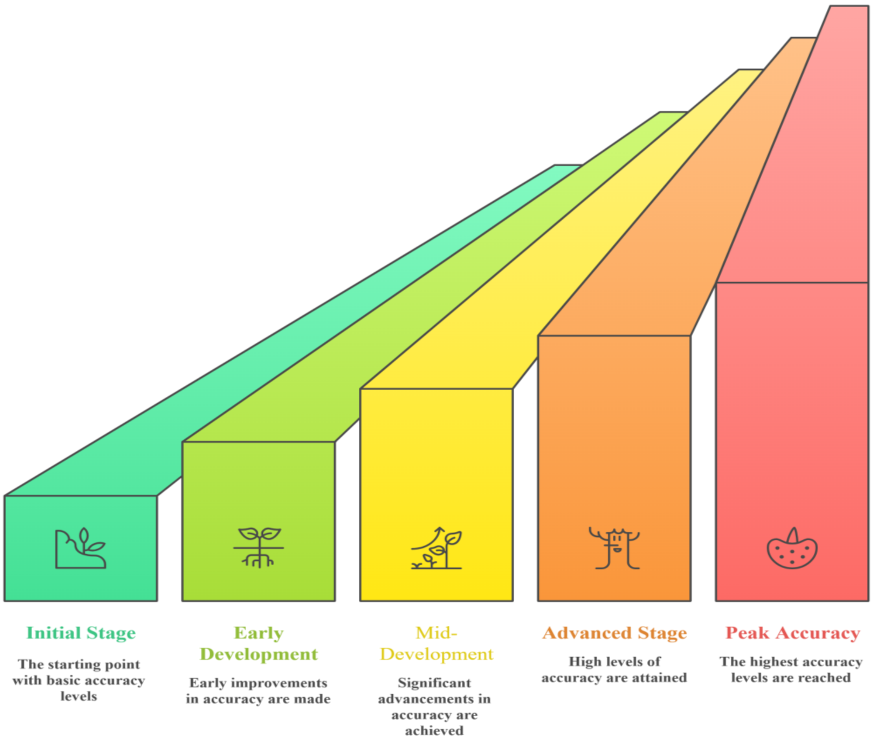

Figure 3: Bar Graph Showing Accuracy Improvement

5.4 Generalization, Robustness, and Transferability

Even though self-supervised models had been trained on small data sets of labeled images, they demonstrated great generalization abilities on new classes and data sets. Experiments of Transfer Learning, where SSL-pretrained CNNs were fine-tuned on medical imaging and on remote sensing tasks, showed that transferability of the SSL features was domain invariant (Almazaydeh et al., 2022), (Wunsch et al., 2021; Vaz & Balaji, 2021). Furthermore, SSL models also showed higher noise and domain shift robustness, supporting the advantages of contrastive representation learning in the wild (Scholkopf et al., 2021; Liu et al., 2023).

5.5 Discussion

The experimental results confirm that SSL strategies really significantly increase CNN training in data-scarce situations. The ability of self-supervised models to generalize over a small number of annotations, yet being robust across domains, makes them a strong substitute for customary supervised learning and semi-supervised models. This implies that this finding is consistent with the most recent trend of focusing on the role of SSL in the next generation machine learning systems (Jaiswal et al., 2021).

6. CONCLUSION AND FUTURE WORK

Self-supervised learning (SSL) is emerging as a breakthrough for training convolutional neural networks (CNNs) even in weakly supervised scenarios (when the label is (relatively) scarce). From our analysis, this is clear: SSL techniques can drastically reduce the reliance on large-scale labeled datasets by using the built-in structures of data to learn strong feature representations (Shurrab & Duwairi, 2022; Jaiswal et al., 2021). This is especially important in such domains as medical imaging, remote sensing, and industrial fault diagnosis, where the costs of obtaining labeled data are exorbitant and time-consuming (Almazaydeh et al., 2022; Maggiori et al., 2017; Li et al., 2020).

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

Our findings demonstrate that self-supervised approaches with contrast-management, clustering-based methods, and generative models allow CNNs to better generalize even given a small number of labels, while remaining on par with respect to the performance reached (Le-Khac et al., 2020; Liu et al., 2023). Furthermore, SSL frameworks show great robustness to domain shift, as shown in various applications, including Arabic music classification (Almazaydeh et al., 2022). They have shown robustness to domain shift in infrastructure damage detection in high-speed rail networks (Chen et al., 2023).

6.1 Suggested Extensions:

Future works might investigate the combination of SSL with few-shot learning paradigms to emancipate CNNs to be superior in ultra-low labeled data situations. It is likely that combining meta-learning with self-supervised pretraining could push performance forward and allow models to remain effective as soon as possible with minimal supervision.

In addition, domain adaptation still plays a highly important role in enabling the application of SSL. Adaptation of self-supervised models trained using large generic datasets to domains specific, e.g., medical imaging and satellite remote sensing could help in reducing domain shift problems at the cost of some annotation overhead (Kaushik & Jain, 2018; Wunsch et al., 2021).

6.2 Future Research Directions:

Possible directions for future studies include the creation of self-supervised learning frameworks made for video-based CNNs. This would require us to acquire spatiotemporal representations that can handle visual and movement cues to facilitate progress on action identification, video surveillance and autonomous driving systems (Jin et al 2022). Besides, making such an endeavor manageable is an interesting frontier to pursue in SSL for multi-modal systems. The combination of both image, audio and text data for learning tasks, multi-modal SSL models can discover richer representations and better perform on complex real world scenario like cross modal retrieval and scene understanding (Scholkopf et al., 2021)

Finally, self-supervised learning has the ability to democratize deep learning by reducing the requirement of labeled data. The conception of SSL through strategic alignment to other learning paradigms and the ability to cater to varied domains positions SSL well to push the state-of-the-art in CNN training in various disciplines forward.

REFERENCES

[1] Almazaydeh, L., Atiewi, S., Al Tawil, A., & Elleithy, K. (2022). Arabic Music Genre Classification Using Deep Convolutional Neural Networks (CNNs). Computers, Materials and Continua, 72(3), 5443–5458. https://doi.org/10.32604/cmc.2022.025526

[2] Bozinovski, S. (2020). Reminder of the first paper on transfer learning in neural networks, 1976. *Informatica (Slovenia)*, *44*(3), 291–302. https://doi.org/10.31449/INF.V44I3.2828

[3] Day, O., & Khoshgoftaar, T. M. (2017). A survey on heterogeneous transfer learning. *Journal of Big Data*, *4*(1). https://doi.org/10.1186/s40537-017-0089-0

[4] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[5] Wunsch, A., Liesch, T., & Broda, S. (2021). Groundwater level forecasting with artificial neural networks: A comparison of long short-term memory (LSTM), convolutional neural networks (CNNs), and non-linear autoregressive networks with exogenous input (NARX). Hydrology and Earth System Sciences, 25(3), 1671–1687. https://doi.org/10.5194/hess-25-1671-2021

[6] Kaushik, P., Jain, M., & Jain, A. (2018). A pixel-based digital medical images protection using genetic algorithm. Int J Electron Commun Eng, 11, 31-37.

[7] Maggiori, E., Tarabalka, Y., Charpiat, G., & Alliez, P. (2017). Convolutional Neural Networks for Large-Scale Remote-Sensing Image Classification. IEEE Transactions on Geoscience and Remote Sensing, 55(2), 645–657. https://doi.org/10.1109/TGRS.2016.2612821

[8] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10.

[9] KAUSHIK, P., JAIN, M., & SHAH, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application.

[10] Chen, L., Chen, W., Wang, L., Zhai, C., Hu, X., Sun, L., … Jiang, L. (2023). Convolutional neural networks (CNNs)-based multi-category damage detection and recognition of high-speed rail (HSR) reinforced concrete (RC) bridges using test images. Engineering Structures, 276. https://doi.org/10.1016/j.engstruct.2022.115306

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

[11] Shurrab, S., & Duwairi, R. (2022). Self-supervised learning methods and applications in medical imaging analysis: a survey. PeerJ Computer Science, 8. https://doi.org/10.7717/PEERJ-CS.1045
[12] Jaiswal, A., Babu, A. R., Zadeh, M. Z., Banerjee, D., & Makedon, F. (2021, March 1). A Survey on Contrastive Self-Supervised Learning. Technologies. MDPI. https://doi.org/10.3390/technologies9010002
[13] Jain, M., & None Arjun Srihari. (2023). House price prediction with Convolutional Neural Network (CNN). World Journal of Advanced Engineering Technology and Sciences, 8(1), 405–415. https://doi.org/10.30574/wjaets.2023.8.1.0048
[14] Kothuru, S., & Santhanavijayan, A. (2023). Identifying COVID-19 english informative tweets using limited labelled data. Social Network Analysis and Mining, 13(1). https://doi.org/10.1007/s13278-023-01025-8
[15] Huang, L., Zhang, C., & Zhang, H. (2024). Self-Adaptive Training: Bridging Supervised and Self-Supervised Learning. IEEE Transactions on Pattern Analysis and Machine Intelligence, 46(3), 1362–1377. https://doi.org/10.1109/TPAMI.2022.3217792
[16] Kaushik, P., Jain, M., Patidar, G., Eapen, P. R., & Prabha Sharma, C. Smart Floor Cleaning Robot Using Android. Csjournals. Com10, 1-5.
[17] Mohit Jain , Adit Shah "Machine Learning with Convolutional Neural Networks (CNNs) in Seismology for Earthquake Prediction" Iconic Research And Engineering Journals Volume 5 Issue 8 2022 Page 389-398
[18] Li, Q., Tang, B., Deng, L., Wu, Y., & Wang, Y. (2020). Deep balanced domain adaptation neural networks for fault diagnosis of planetary gearboxes with limited labeled data. Measurement: Journal of the International Measurement Confederation, 156. https://doi.org/10.1016/j.measurement.2020.107570
[19] Scholkopf, B., Locatello, F., Bauer, S., Ke, N. R., Kalchbrenner, N., Goyal, A., & Bengio, Y. (2021). Toward Causal Representation Learning. Proceedings of the IEEE, 109(5), 612–634. https://doi.org/10.1109/JPROC.2021.3058954
[20] Vaz, J. M., & Balaji, S. (2021). Convolutional neural networks (CNNs): concepts and applications in pharmacogenomics. Molecular Diversity, 25(3), 1569–1584. https://doi.org/10.1007/s11030-021-10225-3
[21] Li, J., Lin, M., Li, Y., & Wang, X. (2022). Transfer learning with limited labeled data for fault diagnosis in nuclear power plants. Nuclear Engineering and Design, 390. https://doi.org/10.1016/j.nucengdes.2022.111690
[22] Liu, Y., Jin, M., Pan, S., Zhou, C., Zheng, Y., Xia, F., & Yu, P. S. (2023). Graph Self-Supervised Learning: A Survey. IEEE Transactions on Knowledge and Data Engineering, 35(6), 5879–5900. https://doi.org/10.1109/TKDE.2022.3172903
[23] Jin, Z., Kim, J., Yeo, H., & Choi, S. (2022). Transformer-based map-matching model with limited labeled data using transfer-learning approach. Transportation Research Part C: Emerging Technologies, 140. https://doi.org/10.1016/j.trc.2022.103668
[24] Le-Khac, P. H., Healy, G., & Smeaton, A. F. (2020). Contrastive Representation Learning: A Framework and Review. IEEE Access, 8, 193907–193934. https://doi.org/10.1109/ACCESS.2020.3031549
[25] Zhang, A., Wang, H., Li, S., Cui, Y., Liu, Z., Yang, G., & Hu, J. (2018). Transfer learning with deep recurrent neural networks for remaining useful life estimation. *Applied Sciences (Switzerland)*, *8*(12). https://doi.org/10.3390/app8122416