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Automated Data Augmentation

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ABSTRACT:

This paper provides an overview of techniques used in automated data collection for image classification based on deep learning. This article first introduces simple data augmentation techniques used in deep learning, followed by a discussion of automatic data augmentation techniques. These methods fall into two categories: research-based methods and educational methods. The search method uses optimization techniques to find the best way to perform data augmentation, while the learning method uses neural networks to learn the best ideas from the data.

This article carefully examines the results of various data representations presented in the literature, including their effects on model accuracy, training time, and computational complexity.

The article also addresses the limitations and challenges of using automatic data augmentation, such as the need for more algorithms to handle more complex data and tasks.

This questionnaire is an important resource for researchers and practitioners interested in augmenting data for deep learning-based image classification. It highlights the strengths and limitations of various automated data augmentation practices and provides insight into best practices for developing effective data augmentation strategies. The authors believe that this research will lead to recent advances in data augmentation and deep learning, resulting in accurate and reliable models for various image classification.

Keywords: deep learning, data augmentation, automatic data augmentation, image classification, search-based method, learning-based methods, optimization, neural networks

Introduction:

deep learning has become an effective tool for solving various computer problems. came Vision operations such as image classification, object detection and segmentation.

The success of deep learning models is mainly due to the large amount of data that enables these models to learn different patterns from the input data.

However, collecting and compiling these datasets can be costly and time- consuming, and sometimes the available data is not enough to inform deep learning models. This has led to interest in data augmentation, which involves creating new models from existing models through multiple transformations to increase the size and diversity of datasets.

Data augmentation has been widely used in computer vision for many years and has been shown to improve the performance of deep learning models in many tasks. However, establishing an effective data augmentation strategy can be difficult as it requires careful consideration of many factors, including dataset type, performance, and learning outcomes.

Additionally, manually creating data augmentation techniques can be time consuming and may not perform well for large datasets.

To overcome the problems of manual data augmentation, automated data augmentation techniques have emerged as a promising approach. These techniques can generate more diverse data with less human intervention, thus improving the performance of deep learning models. In recent years, several automatic data augmentation algorithms have been proposed, each with advantages and limitations.

The purpose of this survey is to provide an overview of various automatic data augmentation algorithms for deep learning-based image classification.

This article focuses on automated processes rather than manually creating changes. It starts with an overview of the basic data augmentation techniques commonly used in deep learning and then discusses the implementation process of data augmentation. Next, this article reviews in detail the experimental results of various data augmentation techniques reported in the literature and summarizes the findings and future directions.

Building blocks of Automated Data Augmentation:

The automatic data growth method may vary in building blocks. However, the process usually involves some equipment.

Data pre-processing is the first building block and includes resizing, normalizing, and cropping data in preparation for magnification. In order to use the magnification process correctly, information should be obtained regularly.

The augmentation function is the transformation of the input data to create a new augmented model. Some examples of editing functions are flip, rotate, scale, shear, and colour adjustment. An optimization algorithm is used to determine the best amplification strategy.

Genetic algorithms, reinforcement learning and Bayesian optimization are some examples of optimization. Finally, an evaluation method is used to evaluate the effectiveness of the augmented data on the objective function. Accuracy, precision, and recall are commonly used criteria for image classification tasks. By combining these building blocks, researchers and practitioners can create data in multiple formats using data augmentation to improve the performance of deep learning models.

Application	**Description**
Medical imaging	**Automated data augmentation techniques have been used to improve the performance of deep learning models for medical image analysis tasks such as tumor detection, classification, and segmentation.**
Remote sensing	**Automated data augmentation techniques have been used to improve the accuracy of deep learning models for remote sensing applications such as land cover classification, object detection, and change detection.**
Autonomous vehicles	**Automated data augmentation techniques have been used to improve the performance of deep learning models for autonomous vehicle applications such as object detection, lane detection, and obstacle avoidance.**
Speech recognition	**Automated data augmentation techniques have been used to generate new training examples for speech recognition tasks such as speaker identification, emotion detection, and speech-to- text conversion.**
Video analysis	**Automated data augmentation techniques have been used to improve the performance of deep learning models for video analysis tasks such as action recognition, object tracking, and video captioning.**

Taxonomy of Image Auto DA Methods:

• Two-stage Methods

Summary table of major AutoDA works reviewed for image classification task

Method	Key technique	Policy optimizer [1]	Stage [2]		Policy optimization [3]		
			two-stage	one- stage	gradient-free	gradient-based	search- free
TANDA[4]	Generative adversarial network	Long short-term	C		C		
AA[5]	Reinforcement learning (RL)	Recurrent neural	C		C		
AWS[6]	Weight sharing ; RL	Proximal policy optimization	C		C		

GAA[7]	Greedy breadth first search	Breadth-first	C	C
PBA[8]	Population-based training	Truncation	C	C
Fast A A[9]	Density Matching L	Bayesian	C	C
PAA[10]	Multi-agent RL	Advantage actor	C	C
AA- KD[11]	Knowledge distillation	-	C	C

Faster AA12	Gradient estimation; Density matching	Stochastic	C	C
RA13	Search space	Grid search	C	
UA14	Augmentation	Uniform	C	
OHL-AA15	Gradient estimation	Stochastic	C	C
Adv AA16	Gradient estimation;	Recurrent	C	C

1Policy optimizer is the algorithm or controller used by AutoDA model to update augmentation strategies during the policy generation stage.

2Classification based on the application sequence of two stages involved. Policy generation and application are performed simultaneously in an one-stage approach, but sequentially in a two-stage method.

3Classification based on the type of policy optimization. Gradient-free methods optimize augmentation policies without approx- imating the gradients of policy hyper-parameters. Gradient-based methods estimates such gradients for policy optimization. Search-free methods re-parameterize the search space to exclude the need of search.

4Transformation Adversarial Networks for Data Augmentations

5AutoAugment

6Augmentation-WiseWeight Sharing

7Greedy AutoAugment 8Population-Based Augmentation

9Fast AutoAugment

10Patch AutoAugment

11AutoAugment with Knowledge Distillation

12FasterAuto

Augment 13RandAugment 14UniformAugmet

15Online Hyper-parameter Learning for Auto-Augmentation

16Adversarial AutoAugment

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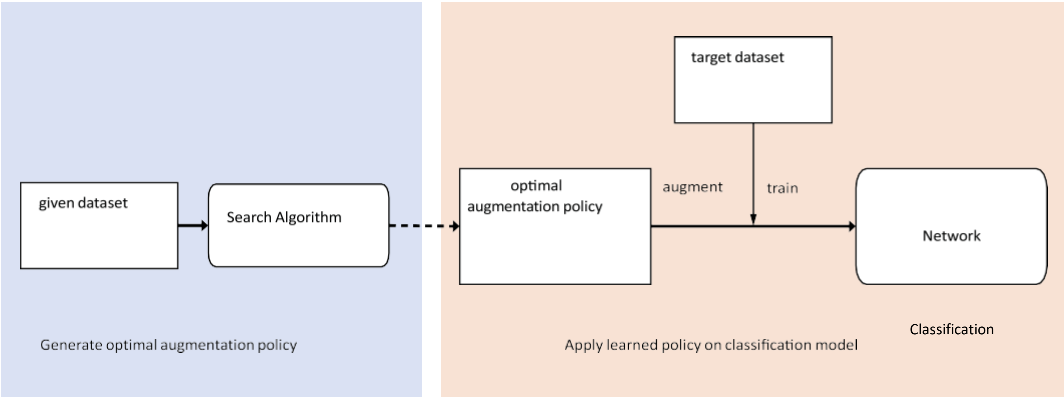

Loopholes :

Although automatic data augmentation techniques can be effective in improving the performance of deep learning models, there are some disadvantages and limitations to consider.

Some disadvantages of using automated data augmentation are:

Overfitting: Automatic data augmentation techniques have produced a lot of new data which increases the risk of overfitting if the model is not regular. It is important to avoid overfitting by using techniques such as releasing, heavy weights, and stopping early.

Quality of generated data: Automatic data augmentation strategies rely on predefined augmentation strategies that cannot capture all changes in input data. This can lead to bad data that does not reflect the accuracy of the data distribution.

Costing: Automatic data augmentation techniques can be expensive, especially if they involve optimization or a large search space.

This can make them difficult to implement in a real-world setting with limited budgets.

Results are easier to interpret: Automatic data augmentation techniques can create new training models that can make model results difficult to interpret. Understanding certain elements or features that contribute to a model's performance can be difficult.

Limitation of change: Automatic data usage process is not well adapted to new data or tasks with different characteristics from old data. This will limit the generalizability of the method.

Although this disadvantage causes difficulties, it is still done to solve them and improve the results of electronic magnification in practice

Conclusion:

Automatic data augmentation has proven to be a very effective technique for improving the performance of deep learning models in many applications. By creating new educational models with augmentation techniques, researchers and practitioners can overcome money constraints or the diversity of educational materials, if so, build the structure. However, there are some limitations and challenges that need to be overcome, such as overuse, poor quality of data produced, high computational costs, difficulties in interpreting results, and restrictions on transitioning to new knowledge or projects. Solving these problems requires continuous research and development, as well as careful consideration of different growing material methods.

However, the use of automatic data augmentation is a promising area of research that could increase the effectiveness and power of deep learning models in many areas such as pain, motor skills, language processing, language skills, and video analysis.

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