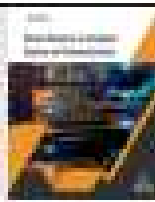


Advancements in Data Augmentation and Transfer Learning: A Comprehensive Survey to Address Data Scarcity Challenges



Salma Fayaz¹, Syed Zubair Ahmad Shah^{1,*}, Nusrat Mohi ud din¹, Nailah Gul¹ and Assif Assad¹

¹Department of Computer Science and Engineering, Islamic University of Science and Technology, Awantipora, Pulwama, Jammu and Kashmir, India

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Abstract: Deep Learning (DL) models have demonstrated remarkable proficiency in image classification and recognition tasks, surpassing human capabilities. The observed enhancement in performance can be attributed to the utilization of extensive datasets. Nevertheless, DL models have huge data requirements. Widening the learning capability of such models from limited samples even today remains a challenge, given the intrinsic constraints of small datasets. The trifecta of challenges, encompassing limited labeled datasets, privacy, poor generalization performance, and the costliness of annotations, further compounds the difficulty in achieving robust model performance. Overcoming the challenge of expanding the learning capabilities of Deep Learning models with limited sample sizes remains a pressing concern even today. To address this critical issue, our study conducts a meticulous examination of established methodologies, such as Data Augmentation and Transfer Learning, which offer promising solutions to data scarcity dilemmas. Data Augmentation, a powerful technique, amplifies the size of small datasets through a diverse array of strategies. These encompass geometric transformations, kernel filter manipulations, neural style transfer amalgamation, random cropping, Generative Adversarial Networks, augmentations in feature space, and adversarial and meta-learning training paradigms.

Furthermore, Transfer Learning emerges as a crucial tool, leveraging pre-trained models to facilitate knowledge transfer between models or enabling the retraining of models on analogous datasets. Through our comprehensive investigation, we provide profound insights into how the synergistic application of these two techniques can significantly enhance the performance of classification tasks, effectively magnifying scarce datasets. This augmentation in data availability not only addresses the immediate challenges posed by limited datasets but also unlocks the full potential of working with Big Data in a new era of possibilities in DL applications.

Keywords: Deep learning, data augmentation, machine learning, transfer learning, convolutional neural network, computer vision.

1. INTRODUCTION

The two most popular and innovative branches of artificial intelligence that are transforming the way humans interact with technology are Machine Learning (ML) and Deep Learning (DL). In ML, the algorithms are used to learn from data and create predictions that can help in decision-making [1]. DL is a specialized area of ML that utilizes Neural Networks (NN) and algorithms to understand complex data and make decisions. ML and DL are broadly used in the areas of natural language processing (NLP) [2], finance and autonomous driving [3], computer vision [4], robotics, and medical management [5]. The technique of artificially enhancing the amount of a dataset by performing various modifications on the already-existing data is known as Data Augmentation.

These transformations include rotation, scaling, cropping, flipping, and color jittering. By introducing these variations, a larger variety of data is available to the model, which can help improve its ability to generalize to new data and reduce overfitting [6].

Transfer learning is a method for using the expertise a model has gained on one task to enhance its performance on another related task. Instead of starting from basics, the starting point is a prototype that is trained previously and the fine-tuning of the model is done on the new task by adjusting the 'pre-trained layer' weights while keeping the remaining of the model frozen. This approach can significantly lessen the quantity of data required for training and how long it takes to train a model from scratch [7]. Data augmentation has been used in image processing for several decades, but its application to models of DL gained popularity from the emergence of convolutional neural networks (CNNs). Similarly, transfer learning has been in use in natural language processing (NLP) for

*Address correspondence to this author at the Department of Computer Science and Engineering, Islamic University of Science and Technology, Awantipora, Pulwama, Jammu and Kashmir, India.
 E-mail: subzshah@iustt.ac.in