論文 / 著書情報
Article / Book Information

題目(和文)	
Title(English)	A Study on Robust Image Classification Networks against Known and Unknown Degradations
著者(和文)	DAULTANI DINESH
Author(English)	Dinesh Daultani
出典(和文)	学位:博士(工学), 学位授与機関:東京工業大学, 報告番号:甲第12849号, 授与年月日:2024年9月20日, 学位の種別:課程博士, 審査員:田中 正行,倉林 大輔,中臺 一博,原 精一郎,川上 玲,奥冨 正敏
Citation(English)	Degree:Doctor (Engineering), Conferring organization: Tokyo Institute of Technology, Report number:甲第12849号, Conferred date:2024/9/20, Degree Type:Course doctor, Examiner:,,,,,
学位種別(和文)	博士論文
Category(English)	Doctoral Thesis
種別(和文)	論文要旨
Type(English)	Summary

（博士課程）
Doctoral Program

論 文 要 旨

THESIS SUMMARY

系・コース： Department of, Graduate major in	Systems and Control Engineering 系 コース	申請学位（専攻分野）： Academic Degree Requested	博士 Doctor of （Engineering）
学生氏名： Student's Name	Daultani Dinesh	審査員主査： Chief Examiner	Masayuki Tanaka

要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

Computer vision has been utilized in diverse applications in our daily lives. However, real-world images often incorporate various types of degradation that hinder the performance of neural networks in different computer vision tasks. These degradations can arise from factors such as camera sensor noise (e.g., Gaussian noise), weather conditions (e.g., rain), and digital image compression (e.g., JPEG artifacts). In practical computer vision applications, such degradations are unavoidable, making it crucial to develop strategies to handle them effectively.

This thesis aims to bridge the gap identified in previous research, where a single network can handle only a specific known degradation. In contrast, this work proposes a single network capable of managing multiple unknown degradations. Primarily, we focus on the image classification task of degraded images. Moreover, this thesis addresses gaps in prior studies by examining a wide range of known and unknown degradations, thereby enhancing the robustness and applicability of neural networks in real-world computer vision scenarios.

First, we investigate the relationship between robust data augmentation techniques and knowledge distillation to enhance the performance of convolution neural networks (CNNs) to classify degraded images. We categorize data augmentation methods into two groups: cut-and-delete methods, which improve the robustness of the network, and geometric-and-color methods, which increase the diversity of the dataset. Our research focuses on determining the optimal positioning of these data augmentation methods and the strategic placement of consistency loss functions during the knowledge distillation. Furthermore, instead of increasing the depth or complexity of the network, we combine knowledge distillation with diverse data augmentation to develop efficient neural networks for degraded image classification. Concretely, we utilize data augmentation methods like RandAugment for geometric-and-color data augmentation and Random Erasing for cut-and-delete data augmentation, improving robustness and performance. Empirical experiments on the CIFAR-10 and CIFAR-100 datasets confirm the effectiveness of our proposed method. Additionally, the significant superiority of our methods on the Tiny ImageNet dataset underscores their efficiency on larger, more realistic datasets.

Next, we address the challenge of requiring multiple networks for different types of degradation. We introduce FusionDistill, a framework based on the fusion of network weights and knowledge distillation. This approach consolidates multiple classifiers, each trained on different degradations, into a robust single network. The resulting network is capable of handling multiple known degradations. Our experiments demonstrate that FusionDistill can effectively manage various known degradations without additional information about the specific degradation at the inference time. Furthermore, our proposed method consistently surpasses previous state-of-the-art pretraining and out-of-distribution generalization methods on the CIFAR-10, CIFAR-100, and Tiny ImageNet datasets. Importantly, our proposed method maintains the performance level of the individual classifiers trained on specific degradations, i.e., the Oracle, ensuring that the consolidated network does not compromise accuracy or efficiency.

Next, we present DiffAUD, a novel diffusion-based adaptation method designed to address unknown degraded images by leveraging a few known degradations and knowledge distillation. We demonstrate that DiffAUD effectively manages different types of single and sequential unknown degradations through extensive experiments on various convolution and transformer-based architectures. Specifically, comprehensive experiments exhibit that our proposed method substantially outperforms the baseline method with identical computational costs. Furthermore, we baseline DiffAUD on standard datasets such as Imagenet-C, widely used in computer vision for robustness studies, a crucial aspect that was absent in previous research.

Lastly, we summarize the contributions of our study and highlight its significance. By reflecting on the broader context of our work, we also identify several potential avenues for future research, suggesting how subsequent investigations might build upon our findings or explore related research questions. Furthermore, we consider the societal impact of our research, discussing how our study could impact human safety and climate.