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МЕТОД ІНКРЕМЕНТАЛЬНОГО НАВЧАННЯ ДЛЯ КЛАСИФІКАЦІЇ ЗОБРАЖЕНЬ В КОМП'ЮТЕРНОМУ ЗОРІ

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ABSTRACT

The paper tests the hypothesis that Continual Learning (CL) methods can improve the performance of a deep learning model in a traditional machine learning scenario. The hypothesis is tested on a parking lot occupancy detection problem, and compared to contemporary solutions that are non-CL based.

Keywords: deep learning, continual learning, incremental learning, CNN, parking, occupancy detection

INTRODUCTION

For decades the researchers everywhere in the world have been trying to model human cognitive behavior in the field of Artificial Intelligence (AI). Many machine learning (ML) methodologies have been proposed, as well as extensively tested and used, to achieve this goal. However, there is at least one feature of a human brain that has proven to be very difficult to model using a machine: the ability to learn continually.

This ability allows humans to improve their knowledge over time with every new experience they come across. It allows humans to still perform better at most tasks in comparison to standard ML models, which are trained once and never improved afterwards. That being said, in the last decade a new paradigm of ML has been gaining scientific interest: incremental learning. This paradigm discards this notion of training a model once and using it in production afterwards and proposes to see the latter stage as a part of the training process, in other words, learning continually from the observed experiences.

In the recent years the field of incremental learning, often also referred to as "continual learning," has been in the peak of research interest. Numerous methods have been proposed that allows a machine to learn from a continuous stream of data. A lot of these methods focus on solving the problem of "catastrophic forgetting," which causes the model to perform worse and worse on old tasks.

Nowadays, most of the research in this field try to use Continual Learning (CL) to solve completely new types of problems – scenarios, that can not be approached using traditional (non-CL) machine learning methods. Here, the Class-Incremental scenario has caught the most attention, in which the model, which is solving a classification task, is expected to learn completely new classes that have not been encountered previously. Similarly, the Task-Incremental scenario attempts to solve different tasks every time. This way the researchers are trying to expand the space of problems that can be solved using AI.

However, to the extent of the author's knowledge, no research has attempted to improve the performance of non-CL models in traditional scenarios using CL. One of such scenarios is the problem of parking lot occupancy detection, which is a binary classification problem in the field of Computer Vision (CV). This problem presents a continual stream of data in the form of video camera feed, and requires the model to classify, whether a parking space is either free or taken. Such continual data stream allows to apply CL in the attempt to improve the performance of the model over time.

The main goal of this paper is to test the hypothesis that a better performance can be achieved in traditional ML scenarios by augmenting already existing solutions with CL methods. To do this, the paper considers the problem of parking lot occupancy detection, explores already existing solutions to this problem, studies CL methods that can be applied in this scenario, proposes a CL-based solution to this problem, and conducts experiments in order to compare the performance of CL-based and non-CL based methods.

The paper consists of three sections.

Section one contains a review of the problem of parking lot occupancy detection, existing solutions to the problem, and discusses Continual Learning methods, which can be applied to this problem.

The second section describes the implementation of the model and specifics of the reproduction of existing solutions.

Experiment results are reported and discussed in the third section.

1 MOTIVATION AND RELATED WORKS

In this section the problem of parking lot occupancy detection is explored, existing solutions are reviewed, and existing continual learning methods are discussed.

1.1 Parking lot occupancy detection

In today's world having your own vehicle has become a social norm. With the ever-increasing number of vehicles on the streets the problem of efficient parking is becoming more and more evident. Drivers in big cities often encounter a problem finding an empty parking space during peak hours. There are many ways to address this problem on a city management scale, such as balancing road traffic, building more parking lots, or encouraging public transport.

On a smaller scale it's possible to improve drivers' quality of life by making parking more convenient. One of the ways to do this is to implement an automated parking management system, which tracks the availability of each parking spot and provides it to the managers of the parking lot, as well as the drivers who may consider using it. This way drivers will have access to the state of each parking lot in advance, which makes planning a lot easier. At the same time, it makes managing a parking lot easier, because a lot of manual work has been automated. Such system could have various additional functionality, which could help improve drivers' lives. Examples of such functionality are number plate tracking, automated payment system, fraud detection, or statistics collection.

In practice such automated systems are partially achieved using sensors that are installed on each parking space. Unfortunately, this solution is often very costly, thus making it impractical in less developed countries. Amato et al. in their article "Car Parking Occupancy Detection Using Smart Camera Networks and Deep Learning" proposed a cheaper solution, which involves using "smart cameras" in conjunction with a Convolutional Neural Network (CNN) model to detect parking space occupancy in real time. [1]

The relevance of this problem has also been highlighted by Kreshchenko and Yushchenko in their article “Parking spot occupancy classification using deep learning.” The need to improve the parking infrastructure arises, which may include increasing the number of parking lots, setting parking fees, and automating certain processes. The authors claim that an excellent way to make parking easier without requiring significant costs is to create a parking information system. In addition, such system is easily scalable, because adding one parking lot to a system only requires adding one or two cameras. [2]

Very recently Paulo de Almeida et al. released a comprehensive review of existing public datasets, created specifically for solving Computer Vision problems for parking lots, as well as scientific works that use such datasets. [3] The authors defined criteria to choose useful datasets, dropping ones that would not be useful in real world scenarios. Finally, the ones that were chosen were PKLot, CNRPark-EXT, and PLds. These datasets include parking lot images, taken from video cameras during some period. The authors conclude that only PLds contains images at night and during snowy weather, though all of them contain sunny, overcast, and rainy weather images. CNRPark-EXT, however, has eleven camera angles available, which is more than the other ones.

De Almeida et al. also compare the results of different feature extraction-based and deep learning-based approaches when solving the problem of parking lot occupancy detection. They specify the performance each work has achieved in the three cases: train and test on the same camera angle, test on a different camera angle but same parking lot, and finally test on a different parking lot. The third variant is the most interesting, as it resembles the real-life scenario the most, provided no additional data needs to be collected when the model is used. In this variant, as expected, the average performance on reproducible works was reported as 91.8%, which is 4.3% lower than the average performance on the first variant. The authors also specify, whether each reviewed work is biased, reproducible, or uses any private datasets, other than the three stated above. Among these experiments one was chosen to reproduce and try to improve using CL methodologies. The chosen one was work by Amato et al., which was reproducible, achieved pretty good results, and was well-documented. [4] The specifics of the reproduction process of the experiment are described in section 2.

1.2 Continual Learning methodology

The ability to expand one's knowledge continually from a stream of experiences is a feature of natural intelligence. Recently, numerous methods have been proposed that allow deep neural networks to achieve such ability. Many of these methods try to solve completely different CL problems, which makes it difficult to compare different CL methods. However, there have been attempts to create a common framework.

According to van de Ven et al., there are three main Continual Learning scenarios: Task-Incremental, Class-Incremental, and Domain-Incremental. [5] Task-Incremental scenario is the most general case, where every consequent task (containing a batch of streaming data) is different. An example of this could be a robot, which gets a command to clean up the floor, and must perform that task as the outcome. In the Class-Incremental scenario each new task might contain new classes that have not been seen previously. For example, a robot is being shown a new object and is told what this object is. Finally, the Domain-Incremental scenario only involves changes in the distribution of data. The main challenges here are domain shift and concept drift. The number of classes stays the same, but the same input data may belong to a different class.

The problem of parking lot occupancy detection does not involve any changes in the number of classes, as it is always two: either busy or free. The data domain, however, changes: in this case the domain is represented by weather, time of day, and the season. Such changes in the domain introduce additional challenge to any form of intelligence: if a human, that has been watching a parking lot only during the day, is suddenly put in a poorly lit nighttime environment, it can become more difficult to do something even as simple as tell whether the parking spot is busy or free. Admittedly, the human eye is good at adapting to gradual changes, which makes it a lot better suited for this kind of job.

Although, it can be argued that it might be possible to teach a machine to adapt to a gradually changing environment, too. In fact, Taufique et al. in their paper “Unsupervised Continual Learning for Gradually Varying Domains” proposed a CL method that performs Unsupervised Domain Adaptation (UDA) in the CL paradigm. The reported results of the proposed method outperform many existing UDA methods. [6]

2 IMPLEMENTATION

2.1 Reproduction

See Appendix B.

2.2 Applying Continual Learning

Unfortunately, due to a lack of time this section has not been completed.

3 RESULTS

Unfortunately, due to a lack of time this section has not been completed.

CONCLUSIONS

This paper attempts to view the paradigm of Continual Learning from a completely new perspective. An attempt has been made to utilize the methodologies of Continual Learning to achieve better performance on traditional problems, as opposed to solving new problems. This suggests that even solutions to problems that are often considered as “already solved” can be further improved by introducing contemporary CL methods.

In the future more work needs to be done to study the potential of such technique.

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APPENDIX A

List of abbreviations

AI	– Artificial Intelligence
CL	– Continual Learning
CNN	– Convolutional Neural Network
CV	– Computer Vision
ML	– Machine Learning

APPENDIX B

Link to the codes

https://colab.research.google.com/drive/1W0lwEor-V9XnHUmgldROdqsk6rxexS1J?usp=sharing