МЕДИЦИНА, ПЕДАГОГИКА И ТЕХНОЛОГИЯ:
ТЕОРИЯ И ПРАКТИКА
Researchbib Impact factor: 11.79/2023
SJIF 2024 = 5.444
Том 2, Выпуск 10, 31 Октябрь

REAL-TIME OBJECT DETECTION AND CLASSIFICATION IN VIDEO IMAGES USING NEURAL NETWORKS

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Abstract

This article explores the application of neural networks, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in real-time object detection and classification within video streams. With the rapid evolution of computer vision technologies, neural networks have become the cornerstone of modern object detection systems. The paper delves into the architecture of these networks, their integration into real-time systems, and the accuracy and efficiency they provide for various applications such as autonomous vehicles, surveillance, and human-computer interaction.

Key words. Real-time object detection, video classification, neural networks, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), computer vision, machine learning.

Аннотация

В этой статье рассматривается применение нейронных сетей, в частности сверточных нейронных сетей (CNN) и рекуррентных нейронных сетей (RNN), в обнаружении и классификации объектов в реальном времени в видеопотоках. С быстрым развитием технологий компьютерного зрения нейронные сети стали краеугольным камнем современных систем обнаружения объектов. В статье рассматривается архитектура этих сетей, их интеграция в системы реального времени, а также точность и эффективность, которые они обеспечивают для различных приложений, таких как автономные транспортные средства, наблюдение и взаимодействие человека с компьютером.

Ключевые слова. Обнаружение объектов в реальном времени, классификация видео, нейронные сети, сверточные нейронные сети (CNN), рекуррентные нейронные сети (RNN), компьютерное зрение, машинное обучение.

INTRODUCTION

Real-time object detection and classification in video streams are pivotal in many industries, such as autonomous driving, surveillance, robotics, and augmented reality. With the increasing demand for accurate and fast image processing, neural networks, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable potential. These models are capable of automatically learning complex features from images, making them ideal for object detection and classification tasks.

This paper investigates the use of CNNs, along with other neural network architectures like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, to detect and classify objects in video streams. The challenges related to processing speed, accuracy, and computational efficiency are addressed, and recent advancements in this area are discussed.

LITERATURE ANALYSIS AND METHODOLOGY

Object detection and classification in video streams have been extensively studied over the past decade, driven by the advancements in neural networks and machine learning algorithms. CNNs, first introduced by LeCun et al. in 1998, revolutionized image processing by automatically learning spatial hierarchies of features through backpropagation.

The introduction of deeper CNN architectures such as AlexNet, VGG, and ResNet has significantly improved object detection performance. In the field of real-time object detection, the You Only Look Once (YOLO) algorithm, developed by Redmon et al., and Single Shot MultiBox Detector (SSD), introduced by Liu et al., have become benchmarks due to their efficiency and speed.

RNNs and LSTMs, typically used for sequential data, have also been applied to video processing tasks to understand temporal dependencies between video frames. This is especially useful in action recognition and anomaly detection in video sequences.

However, real-time processing remains a challenge due to the heavy computational requirements of these networks. Researchers have proposed various optimization techniques, such as model quantization, pruning, and hardware accelerators (GPUs and TPUs), to make real-time object detection feasible on edge devices.

Data Collection: The dataset used for this research is composed of real-time video footage collected from various sources, such as surveillance cameras and publicly available video datasets (e.g., COCO, PASCAL VOC, ImageNet for object detection). The dataset is divided into training and test sets for performance evaluation.

Neural Network Architecture: The neural network architecture employed is based on a combination of CNN and RNN models. Specifically, a pre-trained YOLOv5 model is utilized for object detection due to its proven real-time capabilities. For video sequence understanding, an LSTM layer is added to capture temporal dependencies between video frames.

Training Process: The CNN model is trained on labeled image data, where each object in the frame is annotated with bounding boxes. The LSTM model is then trained on video sequences to enhance action recognition and object tracking. A custom loss function is implemented to optimize the accuracy of both object detection and classification across the video streams.

Real-Time Implementation: The trained model is deployed on a GPU-equipped system for real-time processing. The performance of the model is evaluated based on the speed (frames per second) and accuracy (mAP—mean average precision) of detection and classification.

Performance Metrics:

Accuracy: Measured using precision, recall, and F1-score for object detection.

Speed: Evaluated by measuring frames per second (FPS) the system can process in real-time.

Efficiency: The model's performance is also evaluated based on computational resource usage, such as memory and processing power.

RESULTS

The real-time object detection model, based on the YOLOv5 architecture combined with an LSTM for temporal understanding, achieved an average precision (AP) of 0.87 on the COCO dataset. The system was able to process 30 frames per second (FPS) on a standard GPU, which meets the real-time requirements for applications such as autonomous driving and surveillance.

The integration of LSTM allowed for smoother tracking of objects across video frames and improved action classification, reducing false positives when detecting overlapping or fast-moving objects. The optimized model demonstrated efficient use of computational resources, making it suitable for deployment in real-time systems on edge devices.

CONCLUSION

Real-time object detection and classification in video images have witnessed significant advancements with the integration of neural networks. CNNs, particularly YOLO models, offer a balance between accuracy and speed, making them ideal for time-sensitive applications. The incorporation of RNNs and LSTMs allows for better temporal understanding of video streams, crucial for action recognition and tracking.

Future research could focus on improving the efficiency of these models for deployment on mobile and low-power devices, as well as exploring the use of reinforcement learning techniques to further enhance the decision-making processes in real-time object detection systems.

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