№ 080

Comparing Pretrained Models in Vital Signs Identification Using Deep Learning Object Detection for PreHospital Care

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Introduction

Deep learning has revolutionized medical imaging, extending its impact to prehospital ambulance care. This study evaluates the accuracy of custom-trained deep learning object detection models for identifying vital signs from defibrillator monitor images, specifically addressing challenges posed by small sample sizes and limited hardware resources.

Methodology

- Study compared two open-source pretrained models, SSD MobileNet V2 FPN (SSD) and EfficientDet-D0 (EDet)
- Utilized the programming language Python with TensorFlow and CUDA package.
- A custom dataset of 90 high-resolution images of captured vital signs from a Zoll X series monitor/defibrillator, which is designated for prehospital care.
- Classes of Pulse rate (PR), blood pressure (BP), oxygen saturation (SO2), and date/time(DT) were manually bounded and annotated using LabelImg software.
- Technique of transfer learning was used for model training on a setup Nvidia GeForce RTX 3060 12 gigabytes, 32 gigabytes of RAM and Intel 12th Generation i7-12700F processor.
- Performance assessed using mean average precision (mAP) across confidence thresholds.

Results

Confidence threshold	Accuracy(%)									
	EfficientDet0					SSD Mobilenet v2 FPN				
	PR	BP	SO2	DT	Overall	PR	BP	SO2	DT	Overall
0.1	56.1	62.5	37.0	35.6	47.8	81.8	91.3	70.5	59.0	75.7
0.3	52.1	62.5	21.0	35.6	42.8	76.8	91.3	70.5	59.0	74.4
0.5	41.2	62.5	21.0	28.6	38.3	76.8	91.3	63.6	48.8	70.1
0.7	33.7	57.5	21.0	8	30.1	76.8	91.3	56.6	31.1	64.0
0.9	26.8	57.5	21.0	0	26.3	76.8	91.3	56.6	18.5	60.8

Table 1: Accuracy of EfficientDet0 compared to SSD Mobilenet v2 FPN

Discussion

EDet displayed greater training variability than SSD, which showed more stable learning. SSD's optimized architecture for real-time applications likely contributed to its higher accuracy. Performance degradation at higher confidence thresholds reflects increased model specificity. Future improvements should focus on optimizing training parameters and expanding the dataset size.

Conclusion

SSD outperformed EDet for vital sign detection, indicating its potential for developing automated image-based monitoring tools in prehospital settings. Despite the small dataset, the custom models achieved promising results. Further research is necessary to evaluate performance on different monitors and the feasibility of real-time implementation.

Keywords - Deep learning, Vital signs, Prehospital Care, Programming

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