

Neural Networks for Tool Image Classification

Boas Bamberger¹, Oliver Erlenkaemper² and Fabian Wolf³

Abstract—TODO

I. INTRODUCTION

II. RELATED WORK

TIC hat keiner gemacht, aber Image Classification ist großes Feld = Paper von verwendeten Modellen

III. METHOD

Experiment: Modelle auf Dataset Trainieren und Testen (train, dev, test split) Training Params in Tabell = Batchsize wurde an Ram Size angepasst, dataaugmentation, weight decay, dropout ist out of scope und wurde deshalb nicht verwendet, auch wenn es im original paper verwendet wurde

A. Model Selection

Models: Literaturreview nach Webster and Watsonn = meist verwendete Architekturen = Archetyp der Architektur

B. Dataset Construction

Dataset: Selbsterstellt (sphärisch um Objekt = verschiedene Winkel, verschiedene intergründe). 15.000, 6 klassen diese sind ..., diese sind balanciert (weil accuracy)

IV. EVALUATION

We evaluated the performance of the selected neural networks as described in Section III. The performances of the selected neural networks were measured in accuracy. The accuracy for each neural network is reported in Table I. Among these neural networks, DenseNet-264 performs best for the TIC Dataset. ResNet-152, ResNeXt-101, and DenseNet-264 perform rather similar. Therefore, we conclude that several neural networks are suited for tool image classification.

¹Boas Bamberger is with the Faculty for Business Studies, University of Mannheim, L5 1, 68131 Mannheim bamberger@uni-mannheim.de

²Oliver Erlenkaemper is with the Department for Research and Development, Movilizer GmbH, Konrad-Zuse-Ring 30, 68163 Mannheim oliver.erlenkaemper@honeywell.com

³Fabian Wolf is with the Faculty for Business Informatics, Baden-Württemberg Cooperative State University (DHBW), Coblitzallee 1-9, 68163 Mannheim s172298@student.dhbw-mannheim.de

TABLE I
EXPERIMENT RESULTS

Neural Network	Accuracy in %
VGG-19	72.40
ResNet-152	92.89
ResNeXt-101	94.66
DenseNet-264	97.45
EfficientNet-B7	16.67

V. DISCUSSION

Verschiedene Modelle geeignet, DenseNet-264 best performing only under constraints of this paper (intro) Several neural networks work for TIC = In accordance with related work

Despited differing in structure All use conv layer Similar performing = Conv layers and skip con VGG only conv performs worst = conv is the basis and skip cons boost performance

Efficient Net 16.67% = just guessed, probably due to batchsize of one = loss function fluctuates heavily = impaired convergence

Komplette section Limitations

VI. CONCLUSION

To the best of our knowledge we are the first to do tool image classification zusammenfassung (several nns work for TIC, conv+skip con works good, practical implications: unsere modelle als basis für end2end impl des business scenarios) verbesserungen (architecture search statt konkrete modelle, excluded learning auxiliaries, bigger batchsize for efficient net) future work(more data, implement end2end business scenario)

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