Application Research of Improved Deep Learning Algorithms for Electronic Component Detection and Classification.

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***Abstract*— This work proposes a model to perform the automatic analysis of the first stages of the reverse engineering process, the detection and classification of components.**

For the stage of component detection on the PCB, we propose an approach based on previous works in the field of satellite image analysis. We have introduced new modifications to adapt our model to the characteristics of electronics components.

The classification stage includes research work on different classification strategies. Due to the nature of electronic designs, we have introduced an approach based on uncertainty analysis. In addition, we have analyzed the impact of different strategies for training our model with unbalanced data.

This work also includes the creation of a dataset composed of real circuits obtained from the "*Servicio de Fabricación de Propotipos*" of the IUMA. This dataset has allowed the development of this work and supports a new component classification proposal that focuses on the morphology of its package.

Index Terms* – *electronic component detection; electronic component classification; PCB; uncertainty analysis; deep learning

I. Introduction

The detection and classification of electronic components are essential in the field of electronic repairs. Before repairing any electronic design, it is necessary to have a high level of knowledge about how it works. In most cases, the manufacturer does not provide any information about the circuit, so it's the responsibility of the expert to generate it. The process of fully reverse engineering an electronic system is a time-consuming activity. This process can take up to several days of work for a skilled engineer, which is costly and rarely justifiable.

This work proposes a solution to the first's steps in the process of reverse engineering: the classification and detections of the components on the PCB.

For developing this solution, we generated a dataset composed of real boards information. The analyzed components have been label by a new classification, which we also propose in this work

II. Dataset

The generated dataset is composed of 15 different designs and 3,342 electronic components. The PCB images were obtained with a machine of AOI (Automated Optical Inspection) model OMRON RNS II-pt. This system generates partial pictures of the design that we have combined into one whole image.

For labelling the components, we have generated a process based on o previous developed software in the group, LabPcb.

The proposed classes for the components are base on their morphology instead of their functionality. This approach reduces the insistent variability between different classes shown by previous works [1]. The classification is divided with a tree structure and has three levels. Figure 1 shows the number of components in each of the seven possible classes at level 1 and includes an example component of each class.

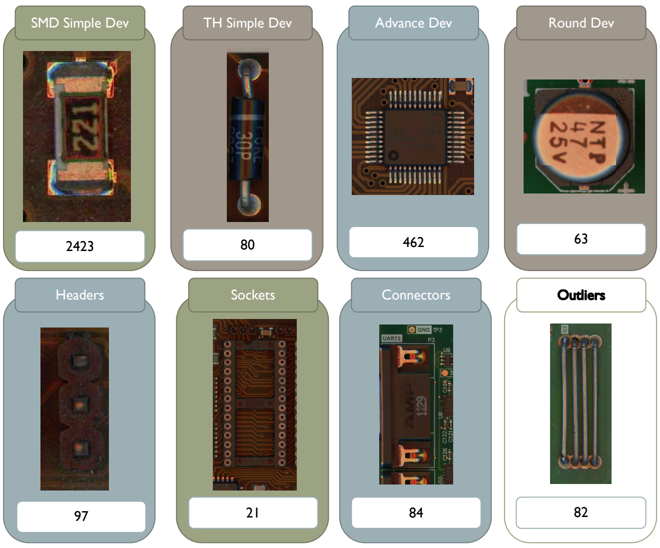

Figure 1: Classification of the components on level 1.

III. System Structure

We propose a system structure with two main stages: detection and classification.

A. Detection Stage

The objective of the detection stage is to identify the location and area of the components on the PCB. The circuit can have a large area (400mmx400mm) while having components as small as 1 mm in length. This characteristic makes traditional solutions to object detection, like YOLO [2], extremely inefficient due to its limited input size.

To solve these inconveniences, we base our work on the solution proposed by YOLT [3] that divides the image into slices and process each independently with YOLO. We have extended this work by introducing higher-level functions to analyze the PCB with different pixel densities and adjusting the configuration of YOLO, for the characteristics of the components.

B. Classifier

The classifier objective is to extract the component probability of belonging to each of the training classes. The classification in the system is done by levels, following the classification tree generated for the dataset.

We have tried two different models for the classification. The first implementation, which was finally chosen for the system, has two stages. First, we use a Feature Extractor based on the DenseNet 121 architecture and then we use a set of SVM classifiers that each is trained to detect one class.

The second implementation is base on a multiclass classifier.

We gave a Bayesian approach by introducing Monte Carlo dropout layers [4] in the model for analyzing the uncertainty of the predictions of each class. Also, we tested different strategies for compensating the imbalance of samples between classes inherent to the nature of the data from electronic components.

C. Metaclassifier

The objective of the metaclassifier in the system is to determine if the components previously classified belonged to the group training classes. The input data comes from 4 different metrics. Then a decision tree determines if the sample is from a class known or unknown for the system. (Figure 2)

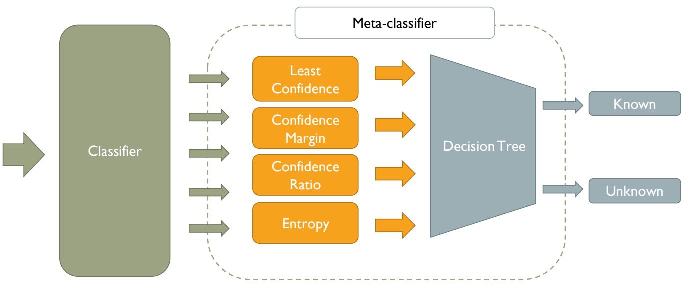

Figure 2: Metaclassifier scheme.

IV. Results

These are the results of the system obtained after selecting the best configuration for each stage:

Table 1: Results of the detection stage.

METRIC	RESULT
Precision	0,941
Recall	0,794

Table 2: Results of the classifiers on the classes of Level 0.

METRIC	RESULT
Accuracy	0,992
Average Precision	0,976
Average Recall	0,979

Table 3: Results of the metaclassifier.

METRIC	RESULT
Average Precision	0,772
Average Recall	0,772

V. Conclusions

We find the results positives just the metaclassifier shows a slightly lower performance. To improve the results of this stage, we are planning to include as input the distribution obtained for each class by Monte Carlo Dropout.

Globally, the results validate the new proposals made on this work. We find potential in this research area for the development of future circular economy technologies for electronics.

References

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