Automated detection of soldering splashes using YOLOv5 algorithm

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***Abstract*—This paper deals with automated visual inspection of electronic boards in serial manufacturing of power electronics devices. Soldering splashes generated in the relevant phases of manufacturing can decrease the quality, parameters and lifetime of hybrid power semiconductor modules. Soldering splashes can occur in restricted area of electronic board and must be removed. Automated inspection is provided using neural network YOLO trained on image dataset of electronic boards acquired by authors in SEMIKRON Slovakia company. Implemented method will lead to higher reliability of manufacturing process.**

***Keywords*—hybrid power semiconductor, soldering splash, visual inspection, convolutional neural network, YOLOv5 algorithm**

I. Introduction

Soldering is currently one of the basic methods of connecting circuit elements. When soldering power modules, it is necessary to ensure a perfect connection of individual components with the baseplate. In practice, it sometimes happens that during the soldering of individual elements there is an imperfect connection of components or splashes are formed.

Splashes most often occur in a two-step soldering process. The first step consists of silicon chips soldering by solder paste and the second step consists of preform soldering of power hybrid to baseplate and terminals.

In a two-step soldering process during the soldering (or re-soldering) of power hybrids to the baseplate, the solder under chips is melted again. Flux is flowing out from solder to the edges of the chips. If there is some restriction or resistance to the flux movement, it can cause an increase in internal mechanical forces and solder splashes (Fig. 1).

Detection of soldering splashes is important for increasing the quality and reliability of power electronic modules and it is important also from economical point of view: most of detected soldering splashes can be removed and electronic board of expensive module can be used again.

II. Materials and Methods

Visual inspection of defects in industrial production is common part of manufacturing process. To increase the reliability of defects detection and decrease the time required for this procedure, modern visual systems and algorithms are implemented last years. Last decade, the computer vision tasks for specific objects detection are based on neural networks (especially convolutional neural networks – CNN). There are some works comparing the modern CNNs and conventional classifiers (such as Support Vector Machine – SVM) used in algorithms for searching specific objects in images. The work [1] concludes that selected CNN obtained better results for identification of given object as method based on SVM.

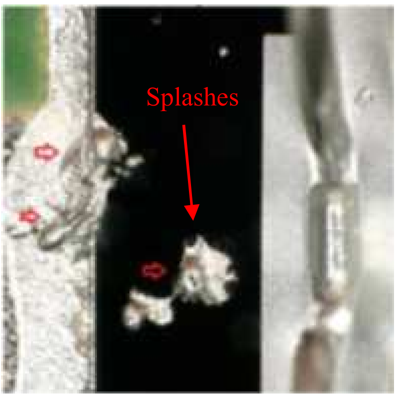

Fig. 1. Typical example of soldering splash.

Deep learning methods achieved promising results in field of machine learning [2]. Deep neural network (DNN) is the core block of many state-of-the art algorithms for object detection. The convolutional neural networks were inspired by biology – especially by work of Hubel and Wiesel about the visual cortex [3]. The way in which input data is processed is the main difference between standard feedforward neural network and convolutional network. Convolutional layer consists of set of filters with learnable coefficients. These filters form the convolutional layers in the CNNs. Training of CNN ideally leads to improvement in patterns recognition [4]. Multilayer feedforward neural networks can be computationally demanding due to high number of weight parameters. The neuronal representation of spatial information can be another bottleneck for flattened layers [5].

Due to significant expansion and massive implementation of CNNs to many image identification tasks, it exists several CNN architectures and their derivatives. In the next part we will discuss about YOLO architectures which was used for our

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application. The research shown their applicability to inspect the electronic boards (PCBs) for different types of defects. The YOLO model (You Only Look Once) belongs to deep neural networks designed by Joseph Redmon as one step process classification algorithm. The input image is divided into a grid *S*x*S*. The YOLO network can detect multiple bounding boxes in single grid cell. In comparison with other deep neural networks, the YOLO's detection speed is relatively high. YOLO can classify multiple categories simultaneously [2]. The final stage of model classification results in localization of bounding box and type of category identification [6]. In our case there is only one object category – soldering splash. YOLO classification model is considered as one of the most successful modifications of Convolutional neural networks [7].

Adibhatla et al. proposed deep learning model based on Tiny-YOLOv2 architecture for PCB quality inspection. Their dataset consisted of 11000 images (420x420 pixels) obtained from the automated optical inspection (AOI) machine. The model achieved 98 % accuracy for batch size 32. YOLO model can have lower recall or increased localization errors than Fast R-CNN network model [5]. YOLO architecture can be preferred due to tradeoff between detection accuracy and speed. The authors consider template-matching and image subtraction as traditional methods for PCB defect detection [8] - [10].

Liao used improved YOLOv4 algorithm for detection of 6 different PCB surface defects – scratch, clutter, broken line, hole loss, line repair damage and over oil-filling. The original dataset consisted of 2008 PCB defect images. The data augmentation was performed, and number of images increased to 19029. Originally 12-megapixel images were resized to 416 x 416 pixels and labelled with LabelImg program. The neural network model with 39.5 million of weight coefficients achieved high performance with 98.6 % mean average precision score (mAP) [11].

We decided to use last version of YOLO model – YOLOv5. It is the most advanced version of this classification algorithm and Python software support is useful in scientific research area. The YOLOv5 medium model was chosen as compromise between detection speed and accuracy.

After the neural network model selection, the training process must be provided. Training process requires a huge dataset of samples. There are many official datasets for various image classification problems, but for detecting soldering splashes we had to create our own dataset. Firstly, the system for image acquisition was selected. Due to relatively small area of soldering splashes, we used high resolution color USB 3.0 camera Basler ace acA4600-10uc with resolution 15 MPix. In the training process the images were not resized to smaller resolution but image was divided into tiles (sub-images). Using resampling the dataset images down, the splashes could disappear from the image.

Camera with cold white LED illumination module was mounted onto adjustable stage to set suitable focus and lightning conditions for image acquisition. Because the research of algorithms for the soldering splashes and other electronic board defects will continue in the future, the images were acquired in color to store as many information as possible. Also the color calibration table was placed in the camera field of view to obtain the possibility of color normalization (white balancing) for the future (Fig. 2).

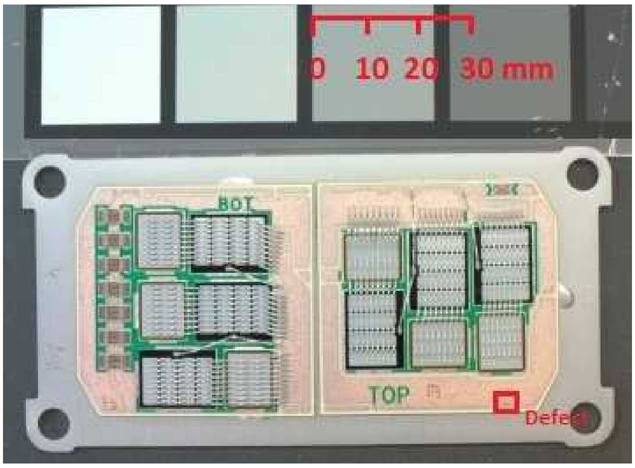

Fig. 2. The dataset sample: electronic board SEMIX with color calibration table and highlighted defect.

The next image processing and training of CNN is discussed in the next section.

III. Experimental Results

As we declared in the previous section, each image in the acquired dataset was annotated by SEMIKRON Company specialist with LabelImg tool dedicated for YOLO. We defined just one class – soldering splash. The original resolution of PCB images was 4608x3288 pixels. The complete dataset actually consists of 231 images and there are 350 soldering splash objects annotated.

Training of YOLO model parameters was accelerated by GPU Nvidia GTX 1070 with 8 GB memory. The PyTorch, CUDA and OpenCV software libraries had to been installed. Due to input images high-resolution quality and large video memory requirements, YOLOv5 neural network model could not been trained on original image resolution [12]. Therefore, the PCB images were tiled with YOLO image tiling script to 640x640 pixels images [13]. Since soldering splashes are objects with relatively small area, it was desirable to preserve object's original resolution. The input dataset was randomly divided into training, validation and testing set in ratios (70% - 20% - 10%).

TABLE I. MODEL PARAMETERS

Initial learning rate	0.0001
Optimizer	Adam
Batch	16
Epochs	1000
Image HSV value augmentation	0.0
Patience	300
Image resolution	640

Initially, the YOLOv5 model was trained with default values of parameters initialized at installation. These parameters were changed in computer simulation experiment to find best originating point for neural network training. Table I shows the values of adjustable parameters for YOLOv5 model that achieved best classification performance. Model learning was repeated for 10 times with this setting.

These model parameters achieved precision 92.7%, recall 87.9% and mean average precision score mAP = 90.6%. Mean average precision parameter describes model accuracy – the higher value indicates more accurate neural network model. For computing the metrics, we used following formulas:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{1}$$

$$Recall = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \tag{2}$$

Formula 1 denotes precision score, where true positives are related to correctly detected soldering splashes and false positives are related to image area incorrectly detected as soldering splashes. Formula 2 denotes recall score, where false negatives are related to undetected soldering splash objects and the rest terms are identical to the terms in formula 1.

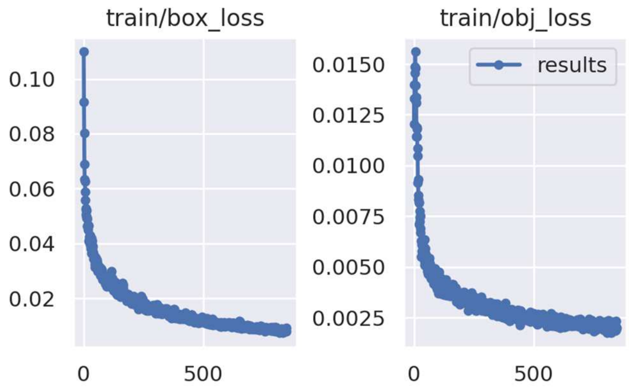

Fig. 3. Plots of objectness and box loss over the training epochs for training set. (Presented graphs are original graphic output of custom YOLOv5 model trained in Python environment and installed from Ultralytics repository [14].)

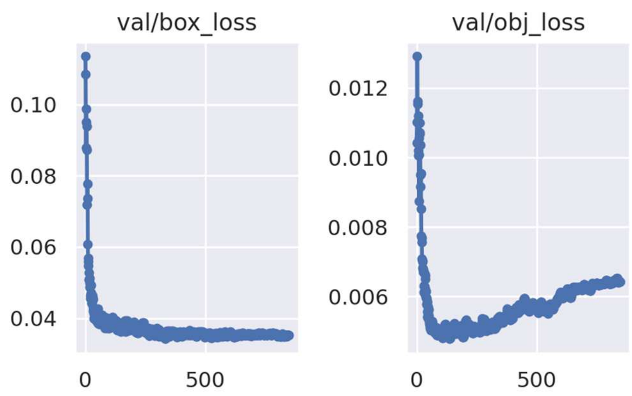

Fig. 4. Plots of objectness and box loss over the training epochs for validation set. (Presented graphs are original graphic output of custom YOLOv5 model trained in Python environment and installed from Ultralytics repository [14].)

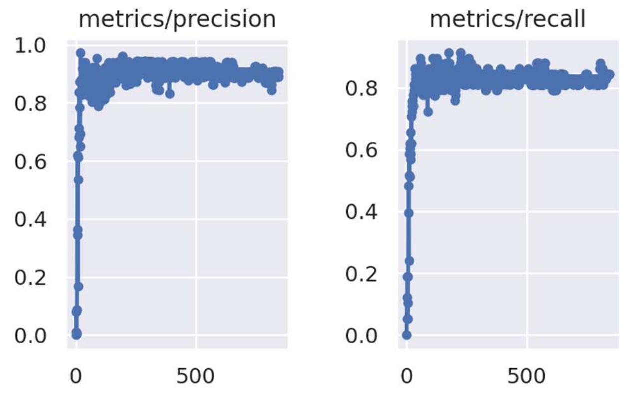

Fig. 5. Plots of precision and recall over the training epochs for training set. (Presented graphs are original graphic output of custom YOLOv5 model trained in Python environment and installed from Ultralytics repository [14].)

The relevant metrics are shown in Fig. 3, Fig. 4 and Fig. 5. The training process shown decreasing trend of normalized box loss score over the epochs for training set (Fig. 3). The box loss function represents how accurate the algorithm can locate the center of an object (soldering splash) and how well the predicted bounding box covers an object. The objectness loss (*obj_loss*) is a measure of the probability that an object exists in a proposed region of interest (ROI) [15].

Fig. 4 shows trend of normalized box loss score over the training epochs. The box loss decreased over the training phase in training and validation set as well. This implies good generalization potential of YOLOv5 model in localization of soldering splash centers. The objectness loss in validation set shown ascending trend after 100 epochs, therefore the training was early stopped.

The precision and recall score were consistently decreasing during training. More images in dataset could potentially lead to increase of the recall score. Fig. 5 shows how the precision and recall score increase over the training epochs. The trained model was detecting soldering blobs with considerable precision.

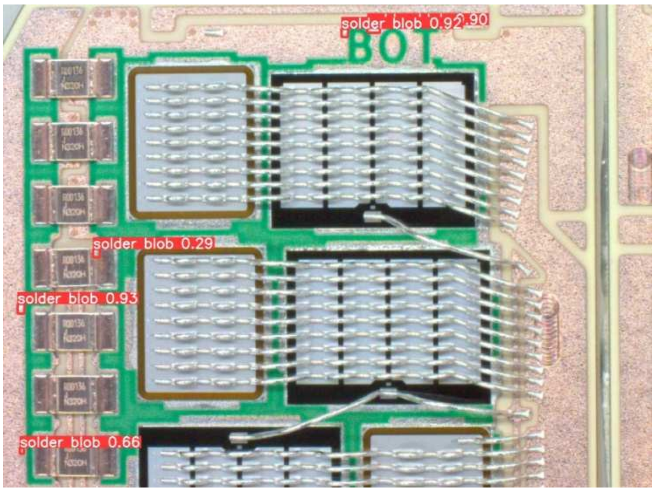

Fig. 6. Example of detected soldering splashes with YOLOv5 model. The solder splashes detected by the computer are marked with red rectangles, numbers indicate confidence score.

The custom trained YOLOv5 model successfully detected even soldering splashes with small area (Fig. 6). These results were obtained from direct implementation of YOLOv5 medium model. There were applied no image transformations and operations. In comparison with soldering splashes, the input images contain many objects with similar color and texture which can degrade classification performance.

IV. Discussion and Conclusion

Despite the fact, YOLOv5 algorithm is not new method, here we present the application of machine learning based object detection in original dataset of specific PCBs. The research shows that YOLOv5 algorithm was successfully used for recognition of objects such as people, cars, animals etc. Application of this algorithm for small objects – soldering splashes – is novel in area.

The first, we created annotated dataset of PCBs (counting 4 types of boards) due to lack of official images of that kind.

The trained neural network model achieved precision of 92.7%. These results can be considered satisfactory using relatively small training set and small area of detected objects. PCB images also contained many objects with color or texture properties similar with soldering splashes – especially wires and bonds.

The classification performance could be potentially increased by using alternative classification model RetinaNet. Enlarging the dataset and increasing the spatial resolution of PCB images can further lead to higher classification score. This will be the subject of further research.

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