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Improving the Performance of Automated Optical Inspection (AOI) Using Machine Learning Classifiers

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***Abstract*—Automated Optical Inspection (AOI) machines inspect the Printed Circuit Board (PCB) manufacturing visually using a camera autonomously scans the device under test for both catastrophic failure (e.g. missing component) and quality defects (e.g. fillet size, shape or component skew). High *false call* rate is a fundamental concern of AOI machines that occurs when a component is considered as a 'fail' incorrectly that then have to be verified manually. In order to alleviate this problem, we train and compare different machine learning models (Decision Tree, Random Forest, K-Nearest Neighbors and Artificial Neural Network) and thresholds using logged fail data and extracting the efficient categorical and numerical features. The results show that the trained classifiers are able to identify the false calls well and increase the accuracy without increasing the error slip much. The K-Nearest Neighbor model, with a low threshold achieves the best result.**

Keywords— Automated Optical Inspection, False Call, K-Nearest Neighbor

I. INTRODUCTION

In the current semiconductor industries, AOI machines are used as quality control measures to achieve the best possible quality. This is mainly because manual inspection tasks are time consuming and costly in high volume production environments. AOIs can be continuously used without fatigue or training human inspectors. Moreover, competition within the industry is growing, and margins are getting lower, so the AOI machines are critical for reducing production costs and losses [5].

Nowadays, AOI machines are widely used in PCB manufacturing. AOI checks the pins on the bottom side of the PCB for the solder quality and the top side of the PCB for missing components and the correct orientation of the components. This is performed with pattern matching and histograms of different colors of lightning which is reflected by the components. Images of these reflections are then captured by multiple cameras stationed at different angles above and under the PCB. AOIs check the locations on the PCB and label the locations as 'fail' when boundary margins are exceeded.

A major problem of the AOIs is the high false call rate that occurs when a component is identified incorrectly as a 'fail'. An experienced operator performs a Manual Optical Inspection (MOI) on the PCBs after the AOI check. The operator has to classify the components that the AOI identifies as 'fail'. In recent literature, this problem is mostly addressed for Surfed Mounted Technology (SMT) production environments [22] [18] [20] [2] [21]. Since AOI technology is in its early phases MOI step is still necessary. The MOI can be phased out eventually when there is enough evidence that the AOI does not miss any errors.

The number of PCBs that need to be inspected is increasing and these false calls result in more work during the MOI and lower reliability for the AOI machine. Each false call can cost around 0.65 cents [17].

This paper aimed to give a possible solution for the problem of false calls related to the solder quality of trough-hole components, as there is not any literature available regarding this problem on these components. We first investigate the features that have a strong influence on false calls. Then we employ the models that can reduce the number of false calls produced by the AOI machine.

We formulated this problem as a binary classification model. Table I. shows the confusion matrix provided for this problem. If both AOI and operator label a component as pass, then it is considered as pass in the confusion matrix (TP). If the AOI label a component as pass, but the operator classifies it as fail, then it is considered as 'escape' (FP). The number of escapes is usually very low for the AOI machines. The component is considered as 'defect' (TN), when both AOI and operator label the component as fail. Locations classified as defect are categorized by some reasons such as 'open', 'presence', 'orientation', 'short' or 'component defect'. If the AOI label a component as fail, but the operator classifies it as pass, then the component is considered as 'false call' (FN).

We investigate different machine learning models consist of Decision tree, Random Forest, K-Nearest Neighbors, and Artificial Neural Network. The models are trained by the fail data logged in the AOI.

They predict the outcome of the MOI with the aim of decreasing the number of false calls of AOI machine in the solder quality of trough hole components without increasing the error slip (escapes). Based on our experiments, the models perform well, with an AUC score higher than 0.8. There is also a trade-off between the false calls and the escapes. The K-Nearest Neighbor model with a low threshold for predicting fails, outperforms other models.

The rest of the paper is organized as follows: In Section II, related works are reviewed; Section III presents our proposed model in detail; Section IV is dedicated to the details of the datasets, experiments and results; and finally, Section V concludes the paper.

TABLE I. CONFUSION MATRIX FOR THE FALSE CALL

		Operator	
		Pass	Fail
AOI	Pass	Pass(TP)	Escape(FP)
	Fail	False Call (FN)	Defect (TN)

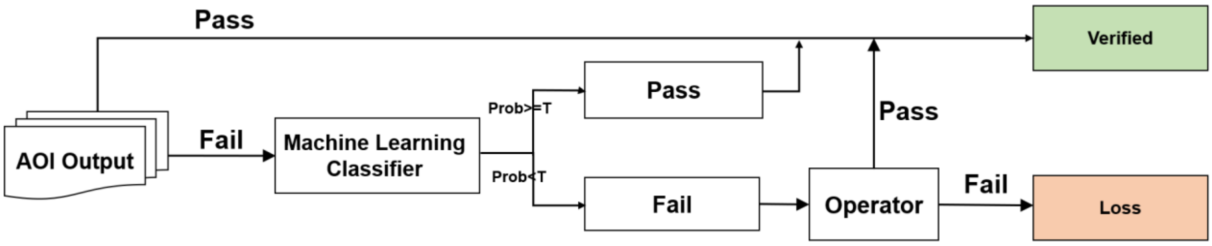

Fig. 1. An overview of the proposed approach

II. Related Work

An electrical or functionality test is essential in earlier steps of the PCB manufacturing process in semiconductor industries. Faults can lead to a shorter life span and loosen the PCB [16]. Furthermore, 80% of the faults that are optically detectable cannot be recognized electrically [2].

The most common defect detecting techniques can be categorized into three different types. The first type is the referential method. This method is based on the AOI scanning the surface of the PCB from different angles. The reflecting of the lighting is then measured and compared with a predefined 'golden image' of the PCB, which can be done with different kinds of algorithms. If the values of the inspection of a region are outside of the set boundaries, then that region is classified as fail. The second type of methods are the non-referential approaches that are not based on a reference picture but design-rule inspection methods. The inspected areas on the PCBs are checked against the specification standards. This has the disadvantage that it misses defects that do not necessarily violate the design rules. The third type of methods are the hybrid approach. This is a combination of the referral and non-referral methods [21].

Some issues during the inspection of the AOI can occur because of different reasons. This is addressed in [9]. One of these reasons is the secularity in solder joint surfaces. This can appear or disappear when a small change in viewing direction occurs. Furthermore, the surface can be illuminated from point light sources. This results in a worse shadowing and consequently a worse classification of this solder joint. Another problem is due to the difference between solder paste and heating that is applied during soldering processes. This variety in the solder applied results in a different shape of the solder joint. Moreover, components are different, and boards are more complex, which makes the development of these recognition process harder.

A study by Jabbar et al. [6] is addressed a similar problem on Surface Mounted Devices (SMD) lines. In this research, they implemented a tree-based solution. When AOI identifies a product as 'false', the model provides the operator a tag (good, false call or defect) with a confidence score. Based on this tag, the operator decides to check this fail or not. The model is developed with the Classification and Regression Tree (CART) and used Random Forest to make a model that uses multiple tree-based models. The RF performs well because it consists of multiple CART decision trees.

In [20], the false call rate is defined as the number of false calls divided by the number of tested signs, and the factors that have a high impact on the false call rate are discussed. It is shown that AOI is limited when relatively normal variations in the process occur. This variation could be a changeover in production or a different supplier of components. The analysis results show that the following factors influence the false call rate: volume of PCB per year, the complexity of the PCB, reproducibility of components, wrappage, PCB substrate, PCB solder resist, and the AOI program.

The false calls of AOI in the SMD line is investigated in [22]. In their research, a machine learning model evaluates the results of the AOI and tries to predict the outcome of the MOI performed by the operator. If the classification probability for the non-defect component surpasses a critical threshold, this component is not be inspected by the operator. Otherwise, the component is checked during the MOI step. These machine learning models are evaluated based on different performance metrics. For small data sets, K-Nearest Neighbors achieved the best result. For large datasets, Artificial Neural Network and Random Forest resulted in better models. In this paper a similar approach for solving the false call problem of AOI in the solder quality of trough-hole components is implemented.

III. Methodology

Forecasting methods have large influence on the development of different artificial intelligent branches consists of Fuzzy Systems [7], Natural Language Processing [12-15] , Expert Systems [3] etc.

Inspired by [22], we proposed a machine learning based model for enhancing the performance of the AOI machine by alleviating the false call problem in the trough hole components of PCBs. The subset of the output labeled as 'fail' by AOI is considered as input of the model. The core of the model is a binary (pass and fail class) machine learning classifier that predicts the results of the operator check. If the classification probability for the pass class is higher than a specific threshold, PCB is not examined by the operator. Otherwise, the PCB is considered as a 'fail' sample and is sent to the operator for further inspection. An overview of the model is shown in Fig. 1. Training data is generated by the output of the AOI machine with the fail label. We apply the Decision Tree, K-Nearest Neighbors, Artificial Neural Network, and Random Forest classifiers. The models are tested on the data set and are evaluated based on different performance metrics.

Decision Tree (DT): Classification and Regression Trees or CART for short is a term to refer to Decision Tree algorithms that can be used for classification or regression predictive modeling problems. Decision Tree solves the problem of machine learning by transforming the data into a tree representation. Each internal node of the tree representation denotes an attribute, and each leaf node denotes a class label. Compared to other algorithms, decision trees require less effort for data preparation during pre-processing [11].

Random Forest (RF): It is a robust machine learning algorithm that can be used for a variety of tasks, including regression and classification. RF makes predictions by averaging over the predictions of several independent base models. The comprehensibility of the approach and its high performance are the advantages of RF. However, RFs become overly complex with an increasing number of training samples [22].

Artificial Neural Network (ANN): An artificial neural network is a machine learning method that consists of multiple layers. Each layer contains nodes and performs a mathematical operation. The nodes in the different layers stimulate neurons in the human brain. From the input layer, the data is passed through the nodes of the different layers and ends in the output layer [1]. ANN is already used in different domains such as speech recognition [8], natural language processing [1], object detection [4], and hand-written word recognition [1, 10].

K-Nearest Neighbors (KNN): The KNN model is a non-parametric, instance-based, and known as lazy learning algorithm since it doesn't learn a discriminative function from the training data but memorizes the training dataset. Each sample is interpreted as a vector, and classification is performed by majority vote calculating the Euclidian distance of the test sample to the neighbor training samples. The k-parameter refers to the number of neighbors used for classifying the new data point [22].

A. *Feature Set*

The performance of the models depends on the choice of the features. For every fail sample, AOI records some information such as the day, order number, serial number and location on the board. About 70% of the fails occur as a result of solder quality [2]. The amount of solder paste can result in a different shape of the solder, which can affect the AOI performance [9]. Therefore, some Selective Wave Soldering (SWS) based parameters are considered in the feature set. Moreover, some PCB properties that influence the false call rate [20], and the data from the components, (e.g., pin length) are included in the feature set.

The features with unique values that are the same for all samples, such as Serial number, product configuration, order number, and product number, are eliminated. Some features are created from the other features. For example, a new feature is created for the length of the pin that sticks out of the board. This feature is created by subtracting the PCB Thickness from the Pin length (PN). The highly correlated features are detected by the Pearson correlation. Furthermore, features that negatively influence the performance of the models are removed. Also, scaling is applied to scale the continuous features and one-hot encoding is used to create dummies variable for categorical features. After applying feature selection algorithms (PCA and K-Best) 36 features are generated. We list in Table II some of the important features that the models use to recognize the class of an input sample.

TABLE II. SOME OF THE FEATURES USED FOR TRAINING THE MODELS

Feature Name	Description
(SWS) Nozzle	Thickness of the nozzle used in the soldering process
(SWS) DIP	1 if the soldering action is a dip action on the pin and 0 if the soldering action is a drag action on the pin
Percentage	Failure percentage output from the AOI machine
(SWS) lowering time	lowering time of the nozzle in the SWS machine (0, 0.5 or 1) 0 indicates that there is no lowering time
Ordersize	Number of the PCB's produced for the order
(SWS) Speed	Speed of the nozzle of the soldering machine
Panel Surface area	The area of the PCB (width x length)
(SWS) Y END	End position on the board

IV. EXPERIMENTAL RESULTS

A. *Dataset*

Among the recorded errors of the AOI, around 0.91 percent is identified as false call. The models are trained only based on the fail data of the AOI. The dataset contains 25440 samples of the fails recorded by the AOI. 70% of these samples (17808) are used as train data and 30% (7632) are used as test data. Missing values are detected and eliminated from the dataset and the remained samples are checked for outliers.

B. *Performance Metrics*

Different metrics are considered for comparing the performance of the models.

Area under the ROC curve (AUC Score): The ROC curve characterizes the trade-off between the true and false positives. AUC scores are convenient to compare the performances of multiple classifiers.

Accuracy: The accuracy of a model is defined as the fraction of the correct predictions to the total predictions [19].

$$Accurcay = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

TABLE III. THE PERFORMANCE OF THE MODELS. THRESHOLDS (T) ARE SHOWN IN THE BRACKETS.

Model	AUC Score	Accuracy	Recall	Absolute error slip (FN)	Pass (TN)
KNN	0.917	0.938	0.87	275	5310
KNN (T=0.01)	-	0.633	0.9929	15	2726
KNN (T=0.001)	-	0.6	0.9934	**14**	2475
CART	0.938	0.951	0.912	193	5250
RF	**0.945**	**0.96**	0.914	182	**5389**
RF (T=0.01)	-	0.825	**0.9982**	25	4197
RF (T=0.001)	-	0.786	0.9896	22	3898
ANN	0.869	0.884	0.833	354	4981
ANN (T=0.01)	-	0.639	0.947	112	2812
ANN (T=0.001)	-	0.419	0.983	37	1116

TABLE IV. THE CONFUSION MATRIX FOR THE MODELS

	KNN		**KNN (T=0.01)**		**KNN (T= 0.001)**		**CART**		**RF**		**RF (T=0.01)**		**RF (T=0.001)**		**ANN**		**ANN (T=0.01)**		**ANN (T=0.001)**	
	Fail	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***	***Fail***	***False call***
Fail	1847	200	2107	2784	2108	3035	2009	180	1940	121	2097	1313	2100	1612	1768	529	2010	2698	2085	4394
False Call	275	5310	15	2726	14	2475	193	5250	182	5389	25	4197	22	3898	354	4981	112	2812	37	1116

Recall: The recall is evaluating the wrongly classified actual positives [19].

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Absolute error slip: The absolute error slip is the total number of FN of the model.

C. Numerical Results and Discussion

In this section, the results of the evaluating of the different models are provided. The models are built and implemented with 5-fold cross-validation using scikit Python. The hyper parameters of the ANN model are tuned based on the default setting in the scikit library.

Table III shows the performance of each model on the dataset. Overall the number of false calls is reduced with the machine learning classifiers. KNN, with K=50, and threshold 0.01 achieves the highest recall. The threshold means that an instance is classified as 'false call' if the probability of belonging to the 'fail' class is lower than 0.01. The absolute error slip is also the lowest for the KNN model, while the number of pass samples (false calls that are not checked anymore) is also lower. Therefore, there is also a trade-off between the false calls and the escapes that need to be considered when the models are implemented. The RF model (with the maximal depth of the tree=42) achieves the highest AUC score and accuracy. The confusion matrix for the models is shown in Table IV.

A lower number of absolute errors results in a lower number of passes. If the KNN (with the threshold 0.001) model is implemented 2475 false calls are correctly predicted, but 14 extra escapes out of the 7632 escapes are generated. Thus, the number of checks the operator must perform is reduced by approximately 0.32 percent (=2475/7632). However, 14 extra escapes are created, and 0.0018 percent of the total inspected instances are escape samples that are not recognized. The KNN model with a threshold of 0.001 is an appropriate model to implement. This is because it results in a low number of escapes but still decreases the number of checks the operator performs by 0.324 percent.

V. CONCLUSION

Employing AOI machines helps the semiconductor industry to achieve high-quality products. PCBs are investigated by AOI, and afterward, an operator checks and classifies the areas on the PCB which are marked as 'fail'. The main problem arises when the AOI produces a lot of false calls. Around 0.91 percent of the predicted fails are classified as false calls during the MOI. This research focuses on the machine learning based classifiers that substitute the manual verification process by predicting pass, false calls of AOI in the solder quality of through hole components.

All the trained models achieve promising results. Considering the trade-off between the fall calls and escapes, KNN classifier is the most reasonable model.

We believe that employing larger datasets and other important features can improve the performance of the models. These models also can be extended for investigating other types of fails.

REFERENCES

[1] O. I. Abiodun, A. Jantan, A. E. Omolara, K. V. Dada, N. A. Mohamed, and H. Arshad, "State-of-the-art in artificial neural network applications: A survey," *Heliyon*, vol. 4, p. e00938, 2018.

[2] G. Acciani, G. Brunetti, and G. Fornarelli, "Application of neural networks in optical inspection and classification of solder joints in surface mount technology," *IEEE Transactions on industrial informatics,* vol. 2, pp. 200-209, 2006.

[3] C. Angeli, "Online expert systems for fault diagnosis in technical processes," *Expert Systems,* vol. 25, pp. 115-132, 2008.

[4] A. Dhillon and G. K. Verma, "Convolutional neural network: a review of models, methodologies and applications to object detection," *Progress in Artificial Intelligence,* vol. 9, pp. 85-112, 2020.

[5] S.-H. Huang and Y.-C. Pan, "Automated visual inspection in the semiconductor industry: A survey," *Computers in industry,* vol. 66, pp. 1-10, 2015.

[6] E. Jabbar, P. Besse, J.-M. Loubes, N. B. Roa, C. Merle, and R. Dettai, "Supervised learning approach for surface-mount device production," in *International Conference on Machine Learning, Optimization, and Data Science*, 2018, pp. 254-263.

[7] R. Kamalian, E. Yeh, Y. Zhang, A. M. Agogino, and H. Takagi, "Reducing human fatigue in interactive evolutionary computation through fuzzy systems and machine learning systems," in *2006 IEEE International Conference on Fuzzy Systems*, 2006, pp. 678-684.

[8] S. Kriman, S. Beliaev, B. Ginsburg, J. Huang, O. Kuchaiev, V. Lavrukhin, R. Leary, J. Li, and Y. Zhang, "Quartznet: Deep automatic speech recognition with 1d time-channel separable convolutions," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 6124-6128.

[9] N. S. S. Mar, P. Yarlagadda, and C. Fookes, "Design and development of automatic visual inspection system for PCB manufacturing," *Robotics and computer-integrated manufacturing,* vol. 27, pp. 949-962, 2011.

[10] M. Ramzan, H. U. Khan, W. Akhtar, A. Zamir, S. M. Awan, M. Ilyas, and A. Mahmood, "A survey on using neural network based algorithms for hand written digit recognition," *environment,* vol. 9, 2018.

[11] V. Reshadat and H. Faili, "A New Open Information Extraction System Using Sentence Difficulty Estimation," *Computing and Informatics,* vol. 38, pp. 986-1008, 2019.

[12] V. Reshadat and M.-R. Feizi-Derakhshi, "Studying of semantic similarity methods in ontology," *Research Journal of Applied Sciences, Engineering and Technology,* vol. 4, pp. 1815-1821, 2012.

[13] V. RESHADAT, M. HOORALI, and H. FAILI, "A Hybrid Method for Open Information Extraction Based on Shallow and Deep Linguistic Analysis," *Interdisciplinary Information Sciences,* vol. 22, pp. 87-100, 2016.

[14] V. Reshadat, M. Hourali, and H. Faili, "Confidence Measure Estimation for Open Information Extraction," *Information Systems & Telecommunication,* p. 1, 2018.

[15] V. Reshadat, T. Kolkman, K. Zervanou, Y. Zhang, and A. Akcay, "Knowledge Modelling and Incident Analysis for Special Cargo," in *Springer*, ed, 2021.

[16] J. Richter, D. Streitferdt, and E. Rozova, "On the development of intelligent optical inspections," in *2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC)*, 2017, pp. 1-6.

[17] O. Ron Ellenbogen, "Cutting down on false alarms. Onboard technology," *Retr*ieved March 12, 2021, from www.onboard-technology.com, 2006.

[18] R. Seidel, H. Amada, J. Fuchs, N. Thielen, K. Schmidt, C. Voigt, and J. Franke, "Data Mining System Architecture for Industrial Internet of Things in Electronics Production," in *2020 IEEE 26th International Symposium for Design and Technology in Electronic Packaging (SIITME)*, 2020, pp. 75-80.

[19] N. Seliya, T. M. Khoshgoftaar, and J. Van Hulse, "A study on the relationships of classifier performance metrics," in *2009 21st IEEE international conference on tools with artificial intelligence*, 2009, pp. 59-66.

[20] R. Soukup, "A methodology for optimization of false call rate in automated optical inspection post reflow," in *33rd International Spring Seminar on Electronics Technology, ISSE 2010*, 2010, pp. 263-267.

[21] E. M. Taha, E. Emary, and K. Moustafa, "Automatic optical inspection for PCB manufacturing: a survey," *International Journal of Scientific and Engineering Research*, vol. 5, pp. 1095-1102, 2014.

[22] N. Thielen, D. Werner, K. Schmidt, R. Seidel, A. Reinhardt, and J. Franke, "A Machine Learning Based Approach to Detect False Calls in SMT Manufacturing," in *2020 43rd International Spring Seminar on Electronics Technology (ISSE)*, 2020, pp. 1-6.