An Ensemble Learning Approach to Chip Defect Detection in Optic Inspection

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***Abstract*—The market of automatic optical inspection systems (AOI) is estimated a billion USD, with a compound annual growth rate of 16% in five years. Traditional approaches are time consuming and costly [1]. Machine learning is expected to solve the problems. A new AI approach to various inspection items for better stability is presented. Based on the proposed concept of ensemble learning, this new algorithm extracts features derived by the three legacy algorithms as the inputs of the proposed defect detection algorithm. Numeric results shows the highest accuracy rate can reach 97% for QFN packages.**

Keywords: AOI, Chip package, Defect detection, Ensemble learning

I. Introduction and Literature review

The design of AOI machines is very time-consuming, it not only requires professional in the field of optical inspection but also the demands are time-varying as packages. The applicability of machine learning (ML) modeling methods, in the past, demonstrates the potentials of ML to solve that problem. Richter *et al.*[2] presented a new architecture, which uses a superposition of active and unsupervised learning to build a problem specific, fully annotated dataset. However, such a database is not feasible enough in some real situations. Kim [3] proposed a CNN-based classification method to extract the chip region and improve the color distribution by the input image transformation. That encourages us to develop deep learning methodology for chip inspection. In this work, an applicable approach for defect detection of chip defects is presented and is evaluated in accuracy and stability of defect detection.

II. Ensemble Learning for Optical Insepection on Chip

Figure 2 is a work flow of this research. An original data set is processed to obtain a complete and an intermediate footprint map data sets. A convolution neural network developed in Model A for defect classification. In model B, an auto-encoder is employed instead to identify defects by the mean square error (MSE). A Gaussian mixture model is established in Model C to use the results of auto-encoder to enhance the AOI performance. Finally, the outputs of the three models are fed to an Ensemble learning model to discover the optimal solution of defect inspection.

III. Experiment Design and Numer Results

In the experiment of model A, image features are extracted by convolution and pooling, and the fully connected layer is connected for training. In the experiment of model B, an autoencoder is used for training, and the mean square error is used to calculate the similarity between the original image and the reconstructed image. In the experiment of model C, the features are extracted from the coiler's self-encoder and substituted into the Gaussian mixture model to obtain the corresponding parameters of density function. In the experiment of the integrated model, the output of the first three models is extracted as a feature, and integrated into a feature data set.

To evaluate the Ensemble model, a 5-fold data test is conducted for cross-validation. The correct rate of the experimental results and the standard deviation are evaluated and shown in Table 1. Obviously, Gaussian Mixture demonstrate a better performance than local outlier factor and principal component analysis (PCA). The earlier numeric results encourage us to explore more concept proofs of various types of defects and packages.

IV. Conclusion

An ensemble learning approach to chip defect detection in optic inspection is presented. Three algorithms, CNN, auto-encoder and Gaussian mixture , contribute the features for an Ensemble model to detect defects of QFN package. Numeric results show a better performance than individual algorithms.

Acknowledgment

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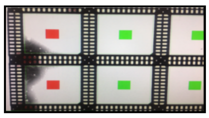

Figure 1 Qualified QFN packages in green and damaged QFN packages in red.

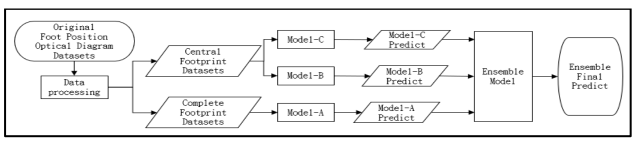

Figure 2 The diagram of the propoaed approach to AOI on QFN packages

Table 1 Comparisons of Various Machine Learning Algorithms

Approach	*Accuracy*	*Standard Deviation*
Gaussian Mixture	97.2%	0.3
Local Outlier Factor	95.7%	1.0
PCA	95.2%	0.4