

# Attention-guided unsupervised representation network for anomaly detection in electronic component manufacturing images

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## ABSTRACT

In modern industrial production, electronic component manufacturing imposes increasingly stringent requirements on quality inspection. To address the susceptibility of traditional detection methods to noise interference, the difficulty of localizing abnormal regions in images, and insufficient feature extraction capability, an improved industrial image anomaly detection method based on the original AGUR-Net (Attention-Guided Unsupervised Representation Network) model is proposed. This method enhances the recognition of abnormal regions by introducing attention gate modules and preactivated fusion residual blocks, while simultaneously combining stacked sparse denoising autoencoders to enhance the model's robustness to noise and suppress redundant information. The experimental results show that the proposed method achieves an accuracy of 84.26 % in locating abnormal regions on the MVTecAD dataset after 185 iterations, which is higher than the dual attention generative adversarial network (79.21 %), long short-term memory non-destructive testing network (79.31 %), and bidirectional long short-term memory network (81.63 %). At 400 iterations, the average loss value of this method for detecting abnormal images of industrial products is 0.016. In addition, the processing time for single images of Class A, B, and C defects in the actual factory environment is 372 ms, 329 ms, and 378 ms, respectively, demonstrating high detection efficiency. Overall, this method can accurately identify and locate abnormal images in the surface treatment and quality inspection stages of electronic component production, which helps to improve the quality control level in the manufacturing process and provides effective technical support for intelligent industrial production.

## ARTICLE INFO

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