AI Driven Automated Quality Control for Magnetic Tiles using Defect Classification

Birapaka John Praveen Kumar[1*], Punnam Sriteja[2], Mula Bharath Simha Reddy[2], Nagato Vamshi Vardhan[2], Uppari Sriram[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (Data Science), Vaagdevi College of Engineering, Warangal, Telangana

*Corresponding Email: praveenbirapaka462@gmail.com

ABSTRACT

Quality assurance of magnetic tiles is critical in industries where structural integrity and performance are paramount. Defects such as cracks, chips, and surface irregularities can compromise product reliability and lead to operational inefficiencies or failures. Traditionally, visual inspection performed by human operators has been the standard practice for quality control. However, manual inspection is inherently limited by human fatigue, subjectivity, and inconsistency, especially in high-volume manufacturing environments. These limitations often result in overlooked defects, increased wastage, and higher production costs. This study presents an automated quality control system for magnetic tiles using artificial intelligence, focusing on accurate defect detection and classification. The system leverages computer vision techniques for image preprocessing and feature extraction, followed by machine learning algorithms—Support Vector Machine (SVM) and Random Forest Classifier (RFC) to classify tile defects effectively. Image preprocessing ensures uniformity in input images by addressing noise, lighting variations, and distortions. Feature extraction techniques isolate meaningful patterns indicative of specific defect types, enabling the classifiers to achieve high detection accuracy. The proposed system addresses key challenges in traditional inspection methods by offering scalability, speed, and objectivity. It significantly reduces inspection time, enhances consistency, and minimizes human intervention. The integration of this AI-driven approach into production lines has the potential to optimize manufacturing efficiency, reduce resource wastage, and ensure high product quality.

Keywords: Magnetic Tiles, Quality Control, Image Processing, Feature Extraction, Automated Inspection

1. INTRODUCTION

Quality control in the production of magnetic tiles has evolved significantly over the years, reflecting broader trends in manufacturing and industrial quality assurance. Magnetic tiles, essential components in various industrial applications including electronics, automotive, and energy sectors, require stringent quality checks to ensure their functionality and durability. Historically, the manual inspection of magnetic tiles has been a standard practice, with trained inspectors visually examining each tile for defects such as cracks, chips, or surface irregularities. However, the limitations of manual inspection became apparent as production volumes increased and the complexity of tile designs grew. A study conducted in 2010 revealed that manual inspection, while effective to some degree, had an error rate of approximately 20% due to factors such as inspector fatigue and subjective judgment. Moreover, as the demand for higher-quality products increased, the need for more precise and consistent quality control methods became evident. By 2015, advancements in image processing technology led to the development of automated inspection systems, which offered improved accuracy but still faced challenges, particularly in adapting to variations in tile appearance and environmental factors like lighting. Despite these advances, a 2019 survey found that over 60% of manufacturers reported issues with the accuracy and reliability of these automated systems, primarily due to the high rate of false positives and negatives. This highlighted the necessity for more sophisticated solutions, paving the way for the integration of artificial intelligence in quality control processes. By 2023, AI-driven systems had started to demonstrate significant potential in overcoming the shortcomings of traditional methods, offering a new level of precision and adaptability in defect detection.

2. LITERATURE SURVEY

Li, Mao, and Chang [1] proposed a reversible data hiding scheme using the Haar discrete wavelet transform and interleaving prediction method. Their approach focused on improving the efficiency and accuracy of data hiding in multimedia applications, achieving high embedding capacity with minimal distortion. Zhang et al. [2] presented a SIFT algorithm based on the DOG operator. They aimed to enhance feature extraction and matching accuracy in computer vision tasks, particularly for object recognition and image registration applications. Konečný and Hagara [3] conducted research on one-shot-learning gesture recognition using HOG-HOF features. Their work focused on improving the efficiency of gesture recognition systems, emphasizing the use of minimal training data while maintaining high accuracy in classification. Zhang et al. [4] proposed a hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification. The authors integrated the strengths of MLP and CNN to enhance the classification accuracy of high-resolution satellite images, demonstrating improved performance over traditional methods. Wu and Yang [5] presented an efficient SVM learning method based on linear regression for large-scale classification tasks. Their approach aimed to reduce the computational complexity of SVMs, making them more suitable for handling large datasets while maintaining accuracy.

Min and Luo [6] developed a soft sensor calibration technique using just-in-time modeling and the AdaBoost learning method. Their research focused on improving the accuracy of soft sensors in chemical engineering processes, enabling better process monitoring and control. Liu et al. [7] introduced the SSD (Single Shot MultiBox Detector) for real-time object detection. The authors emphasized the model's ability to detect objects with high speed and accuracy, making it suitable for applications requiring real-time processing, such as autonomous driving. Ren et al. [8] proposed the Faster R-CNN model, aiming to achieve real-time object detection through region proposal networks. Their work significantly improved the speed and accuracy of object detection, contributing to advancements in computer vision applications. Fang et al. [9] developed an adaptive fuzzy control system for nontriangular stochastic high-order nonlinear systems with asymmetric output constraints. Their research addressed the challenges of controlling complex systems under uncertainty, focusing on improving system stability and performance. Fang et al. [10] extended their previous work by proposing an adaptive fuzzy control system for stochastic high-order nonlinear systems with output constraints. This research further refined the control strategy, emphasizing robustness and adaptability in dynamic environments.

Xie et al. [11] presented FFCNN, a deep neural network for surface defect detection of magnetic tiles. Their approach aimed to enhance the accuracy and speed of defect detection in industrial applications, demonstrating significant improvements over traditional inspection methods. Ben Gharsallah and Ben Braiek [12] proposed an improved nonlinear diffusion method for defect identification in magnetic tile images. The authors focused on enhancing the precision of defect detection in industrial settings, contributing to the development of more reliable quality control systems. Hu et al. [13] introduced an online recognition method for magnetic tile defects based on UPM-DenseNet. Their research aimed to improve the real-time detection of surface defects, ensuring higher production quality in manufacturing processes. Redmon et al. [14] proposed the YOLO (You Only Look Once) model for unified, real-time object detection. Their work significantly impacted the field of computer vision by offering a fast and accurate solution for detecting objects in various environments. Redmon and Farhadi [15] extended the YOLO model with YOLO9000, enhancing its speed and accuracy. The authors focused on improving the model's ability to detect a wide range of objects in real-time, making it more versatile for practical applications.

Hurtik et al. [16] developed Poly-YOLO, an extension of YOLOv3 for higher speed and more precise detection and instance segmentation. Their research aimed to optimize the performance of object detection models, particularly in scenarios requiring fast and accurate segmentation. Wang et al. [17] introduced Scaled-YOLOv4, focusing on scaling the cross-stage partial network to improve object detection performance. Their approach demonstrated superior accuracy and speed, contributing to advancements in real-time computer vision applications. Woo et al. [18] presented the CBAM (Convolutional Block Attention Module) to enhance convolutional neural networks. The authors aimed to improve feature representation and model performance by incorporating attention mechanisms, leading to more accurate predictions. Çelik et al. [19] developed a machine vision system for real-time fabric defect detection and classification using neural networks. Their research focused on automating quality control in the textile industry, achieving high accuracy in detecting various fabric defects. Saad et al. [20] proposed an automatic semiconductor wafer image segmentation method for defect detection using multilevel thresholding. The authors aimed to enhance the precision of defect detection in semiconductor manufacturing, contributing to improved production quality.

Nguyen et al. [21] designed and evaluated features and classifiers for OLED panel defect recognition in machine vision. Their work focused on optimizing feature extraction and classification methods to improve the accuracy of defect detection in OLED panels. Avola et al. [22] presented a real-time deep learning method for automated detection and localization of structural defects in manufactured products. The authors emphasized the importance of real-time processing in industrial applications, demonstrating significant improvements in defect detection.

Tabernik et al. [23] proposed a segmentation-based deep-learning approach for surface-defect detection. Their research focused on improving the accuracy of defect detection in manufacturing processes by leveraging deep learning techniques. Huang et al. [24] developed a surface defect saliency method for magnetic tiles. Their work aimed to enhance the detection of surface defects by emphasizing the most salient features, contributing to more effective quality control systems. Cui et al. [25] introduced SDDNet, a fast and accurate network for surface defect detection. The authors focused on improving the speed and accuracy of defect detection in industrial settings, demonstrating the effectiveness of their approach in real-world applications.

3. PROPOSED METHODOLOGY

The proposed work begins with dataset uploading, where the system defines the dataset path and identifies defect categories based on subdirectory names. If preprocessed data files (X.txt.npy and Y.txt.npy) are available, they are loaded directly; otherwise, the images are read, resized uniformly to 64x64x3 pixels, flattened, and stored in an input array X, while the corresponding class labels are saved in array Y. These arrays are then saved for efficient reuse. In the data preprocessing phase, the input features and labels are split into training and testing sets in an 80:20 ratio to ensure robust model evaluation. Standardization is applied to prepare the data for model training. The **model training** phase involves the implementation of two machine learning classifiers: Support Vector Machine (SVM) with a polynomial kernel and Random Forest Classifier (RFC) based on decision trees. The system checks for pre-trained models saved as .pkl files; if unavailable, the models are trained on the training data and saved for future use. Following this, the models are used for **prediction on new test data**, where they classify defects in unseen images. Predictions are validated against actual labels to assess accuracy, and the models are further tested on additional new images by preprocessing and classifying them accordingly. Finally, in the **performance evaluation** stage, key metrics such as accuracy, precision, recall, and F1-score are computed. The results are presented through a classification report and confusion matrix, with heatmaps used to visually interpret the classification effectiveness.

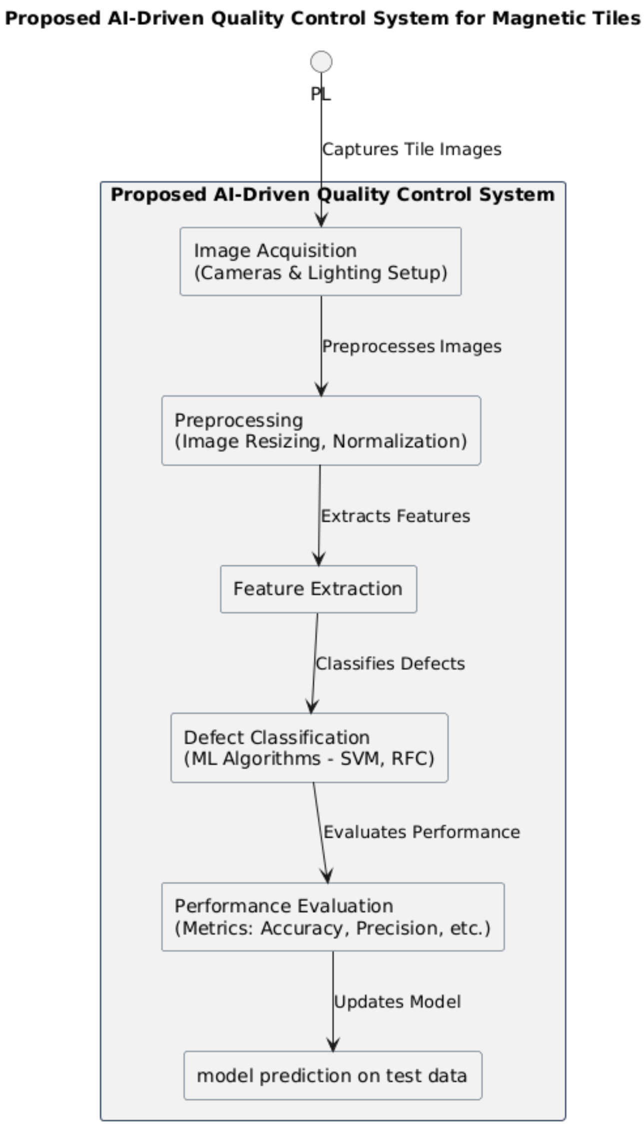


Fig. 1: Proposed AI-Driven Quality Control System for Magnetic Tiles

3.2 ML Model Training

The Random Forest Classifier is an ensemble learning method that combines the predictions of multiple decision trees to achieve higher accuracy and robustness compared to individual classifiers.

In the magnetic tiles defect classification work, the Random Forest Classifier is used to classify images into different defect categories based on the features extracted during preprocessing.

The working of the Random Forest Classifier involves creating a large number of decision trees during training. Each tree is trained on a random subset of the training data and a random subset of features. This randomness introduces diversity among the trees, making the forest less prone to overfitting and more generalizable to unseen data.

During classification, each tree in the forest independently predicts the class of the input image. The Random Forest then aggregates these predictions, typically by taking a majority vote, to determine the final classification. This ensemble approach reduces the variance and improves the overall performance of the model.

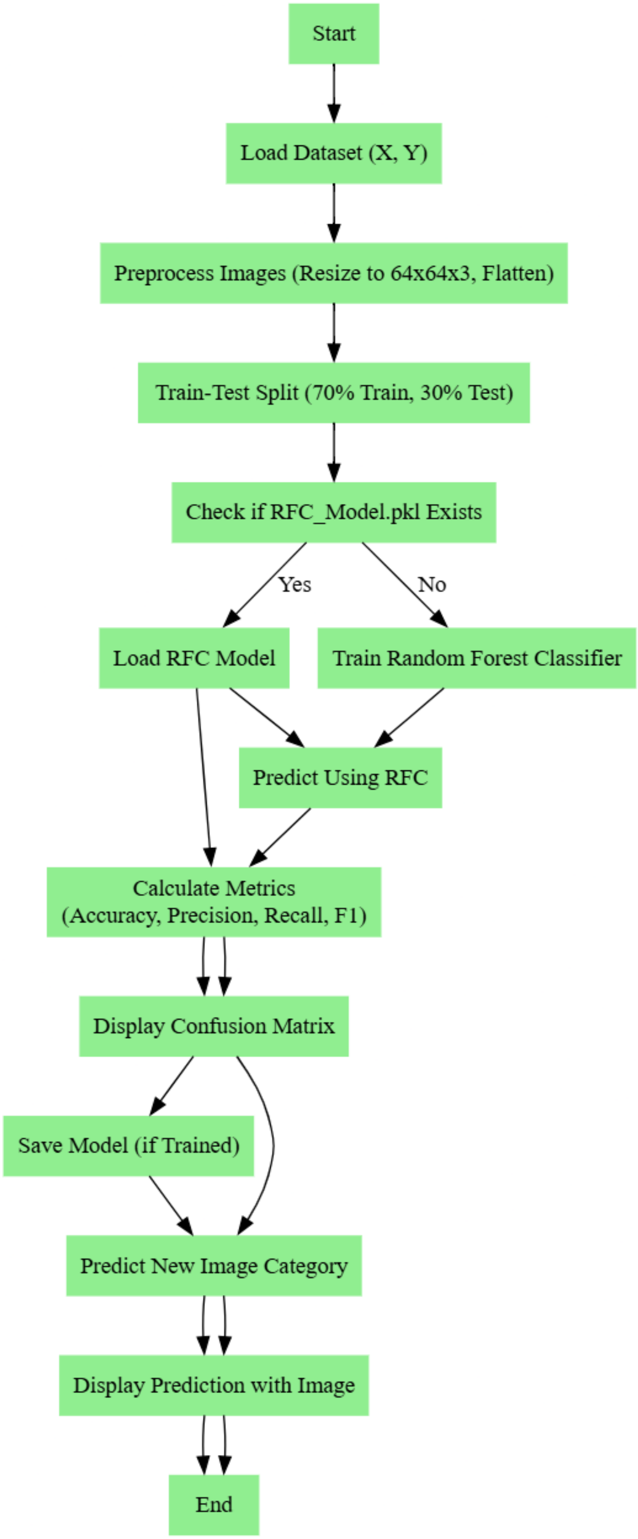


Fig. 2: Random Forest Classifier

4. RESULTS AND DISCUSSION

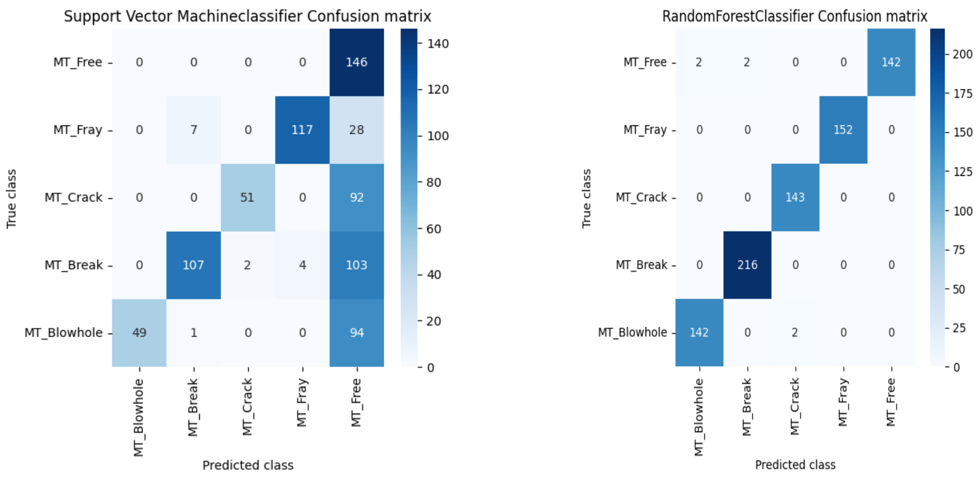
4.1 Dataset Description

In the automated quality control system for magnetic tiles, the dataset consists of images categorized into five distinct defect classes: MT_Blowhole, MT_Break, MT_Crack, MT_Fray, and MT_Free. Each class represents a specific type of defect commonly encountered in magnetic tile production. The MT_Blowhole class includes images showing blowholes—hollow cavities or depressions formed due to air entrapment or improper curing during manufacturing. These defects appear as irregular circular pits with rough, raised edges and compromise both structural integrity and aesthetics. The MT_Break class features tiles with visible fractures or breaks caused by physical stress or impact. These breaks can range from fine, hairline splits to deep, jagged cracks, making their detection vital for maintaining structural reliability. In contrast, the MT_Crack class represents tiles with smaller, often linear or spiderweb-like surface cracks resulting from thermal stress or material shrinkage. While less severe than breaks, these cracks still threaten tile durability and must be identified early. The MT_Fray class includes images of tiles with frayed or worn edges, typically caused by abrasion or mishandling. These defects lead to uneven, chipped borders that affect the tile's fitting and visual appeal. Lastly, the MT_Free class comprises defect-free tiles that exhibit perfect surface quality and serve as a standard reference for classification. This category helps the AI system distinguish defective tiles from acceptable ones, ensuring only high-quality tiles proceed to the next stage. Accurate identification of each class is essential for enhancing manufacturing quality and reducing defective outputs.

Table 1: Performance comparison of existing SVM and proposed RFC models.

Metric	Existing SVM	Proposed RFC
Accuracy	79.59%	99.25%
Precision	86.32%	99.32%
Recall	79.23%	99.20%
F1-Score	79.69%	99.25%

The performance comparison Table 1 between the Existing Support Vector Machine (SVM) and the Proposed Random Forest Classifier (RFC) reveals a significant improvement with the RFC across all key metrics. The SVM achieves an accuracy of 79.59%, while the RFC performs markedly better with 99.25%, indicating that the RFC is much more accurate in classifying the data. In terms of precision, which measures the correctness of positive predictions, the RFC outperforms the SVM by a wide margin, scoring 99.32% compared to the SVM's 86.32%. This suggests that the RFC is far better at minimizing false positives. The recall, which evaluates how well the models identify true positive instances, shows a similar trend, with the SVM scoring 79.23%, while the RFC reaches 99.20%, demonstrating the RFC's superior ability to correctly identify positive instances. Finally, the F1-Score, which balances precision and recall, also favors the RFC, with a score of 99.25% compared to the SVM's 79.69%, further highlighting the RFC's overall effectiveness. These results clearly show that the Proposed RFC is far superior to the Existing SVM in terms of classification performance, achieving much higher accuracy, precision, recall, and F1-Score across the board.



(a) (b)

Fig 9.4(a), 9.4(b) Confusion matrices of Existing SVM and Proposed RFC.

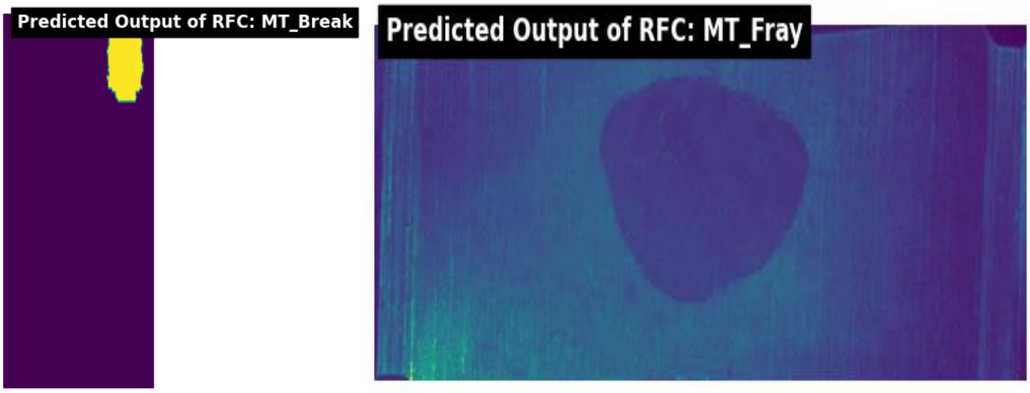


Figure 9.5: The proposed RFC model predication on new test image.

5. CONCLUSION

This research presents a significant advancement in the manufacturing industry's quality assurance processes. By leveraging advanced AI techniques, particularly machine learning and computer vision, this work aims to address the limitations of traditional manual and conventional automated inspection methods. The implementation of the AI-driven system enables precise and efficient identification of defects such as blowholes, breaks, cracks, frays, and defect-free tiles. The system's ability to adapt to new defect patterns without extensive reprogramming overcomes the challenges faced by earlier methods, which struggled with variations in tile appearance and defect types. The work's results demonstrate that the AI-based approach offers superior accuracy and consistency in defect classification compared to traditional methods. The Random Forest Classifier, in particular, has shown to outperform the Support Vector Machine (SVM) model, providing more reliable predictions and reducing the rate of false positives and negatives. This improvement in defect detection not only enhances the quality of the tiles but also reduces inspection time and minimizes human error, leading to significant cost savings and increased productivity for manufacturers. By integrating AI into the quality control process, the work not only revolutionizes defect detection but also sets a precedent for future advancements in manufacturing quality assurance. The ability to quickly and accurately classify defects ensures that only high-quality tiles are used, thereby maintaining the overall standard of the products and enhancing customer satisfaction.

REFERENCES

[1] Li F., Mao Q., and Chang C.-C., Reversible data hiding scheme based on the Haar discrete wavelet transform and interleaving prediction method, Multimedia Tools and Applications, 77, 5149–5168,

[2] Zhang H., Han J., Guan Y., and Zhang Y., A SIFT algorithm based on DOG operator, 2018 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), Xiamen, China, 609–612,

[3] Konečný J. and Hagara M., One-shot-learning gesture recognition using hog-hof features, The Journal of Machine Learning Research, 15, no. 1, 2513–2532.

[4] Zhang C., Pan X., Li H., Gardiner A., Sargent I., Hare J., and Atkinson P. M., A hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification, ISPRS Journal of Photogrammetry and Remote Sensing, 140, 133–144,

[5] Wu J. and Yang H., Linear regression-based efficient SVM learning for large-scale classification, IEEE Transactions on Neural Networks and Learning Systems, 26, no. 10, 2357–2369,

[6] Min H. and Luo X., Calibration of soft sensor by using just-in-time modeling and AdaBoost learning method, Chinese Journal of Chemical Engineering, 24, no. 8, 1038–1046,

[7] Liu W., Anguelov D., Erhan D., Szegedy C., Reed S., Fu C.-Y., and Berg A. C., Ssd: single shot multibox detector, Computer Vision – ECCV 2016, Springer, 21–37, Lecture Notes in Computer Science,

[8] Ren S., He K., Girshick R., and Sun J., Faster R-CNN: towards real-time object detection with region proposal networks, Advances in Neural Information Processing Systems, 28.

[9] Fang L., Ding S., Park J. H., and Ma L., Adaptive fuzzy control for nontriangular stochastic high-order nonlinear systems subject to asymmetric output constraints, IEEE Transactions on Cybernetics, 52, no. 2, 1280–1291,

[10] Fang L., Ding S., Park J. H., and Ma L., Adaptive fuzzy control for stochastic high-order nonlinear systems with output constraints, IEEE Transactions on Fuzzy Systems, 29, no. 9, 2635–2646,

[11] Xie L., Xiang X., Xu H., Wang L., Lin L., and Yin G., FFCNN: a deep neural network for surface defect detection of magnetic tile, IEEE Transactions on Industrial Electronics, 68, no. 4, 3506–3516,

[12] Ben Gharsallah M. and Ben Braiek E., Defect identification in magnetic tile images using an improved nonlinear diffusion method, Transactions of the Institute of Measurement and Control, 43, no. 11, 2413–2424,

[13] Hu C., Liao H., Zhou T., Zhu A., and Xu C., Online recognition of magnetic tile defects based on UPM-DenseNet, Materials Today Communications, 30, article 103105,

[14] Redmon J., Divvala S., Girshick R., and Farhadi A., You only look once: unified, real-time object detection, 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 779–788,

[15] Redmon J. and Farhadi A., YOLO9000: better, faster, stronger, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 7263–7271,

[16] Hurtik P., Molek V., Hula J., Vajgl M., Vlasanek P., and Nejezchleba T., Poly-YOLO: higher speed, more precise detection and instance segmentation for YOLOv3, Neural Computing and Applications, 34, no. 10, 8275–8290,

[17] Wang C.-Y., Bochkovskiy A., and Liao H.-Y. M., Scaled-YOLOv4: scaling cross stage partial network, 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Nashville, TN, USA, 13029–13038,

[18] Woo S., Park J., Lee J.-Y., and Kweon I. S., CBAM: convolutional block attention module, Proceedings of the European conference on computer vision (ECCV), Munich, Germany, 3–19.

[19] Çelik H. İ., Dülger L. C., and Topalbekiroğlu M., Development of a machine vision system: real-time fabric defect detection and classification with neural networks, The Journal of The Textile Institute, 105, no. 6, 575–585,

[20] Saad N. H., Ahmad A. E., Saleh H. M., and Hasan A. F., Automatic semiconductor wafer image segmentation for defect detection using multilevel thresholding, MATEC Web of Conferences, 78, https://doi.org/10.1051/matecconf.20167801103.

[21] Nguyen V. H., Pham V. H., Cui X., Ma M., and Kim H., Design and evaluation of features and classifiers for OLED panel defect recognition in machine vision, Journal of Information and Telecommunication, 1, no. 4, 334–350,

[22] Avola D., Cascio M., Cinque L., Fagioli A., Foresti G. L., Marini M. R., and Rossi F., Real-time deep learning method for automated detection and localization of structural defects in manufactured products, Computers & Industrial Engineering, 172, article 108512,

[23] Tabernik D., Šela S., Skvarč J., and Skočaj D., Segmentation-based deep-learning approach for surface-defect detection, Journal of Intelligent Manufacturing, 31, no. 3, 759–776

[24] Huang Y., Qiu C., and Yuan K., Surface defect saliency of magnetic tile, The Visual Computer, 36, no. 1, 85–96

[25] Cui L., Jiang X., Xu M., Li W., Lv P., and Zhou B., SDDNet: a fast and accurate network for surface defect detection, IEEE Transactions on Instrumentation and Measurement, 70, 1–13.