Automated defect detection in submersible pump impellers using image classification

Deepa Somasundaram[1], V. Pramila[2], G. Ezhilarasi[3], D. Lakshmi[4], P. Kavitha[5], R. Kalaivani[6]
[1]Department of Electrical and Electronic Engineering, Panimalar Engineering College, Tamilnadu, India
[2]Department of Electrical and Electronic Engineering, B.S.A. Crescent Institute of Science and Technology College, Chennai, India
[3]Department of Electrical and Electronic Engineering, Sri Sairam Institute of Technology, Chennai, India
[4]Department of Electrical and Electronic Engineering, Academy of Maritime Education and Training, Chennai, India
[5]Department of Electrical and Electronic Engineering, R.M.K Engineering College, Chennai, India
[6]Department of Electrical and Electronic Engineering, Rajalakshmi Engineering College, Chennai, India

Article Info

Article history:

Received Sep 30, 2024
Revised Apr 11, 2025
Accepted Jul 3, 2025

Keywords:

Convolutional neural networks
Deep learning
Defect detection
Non-destructive testing
Submersible pump impellers

ABSTRACT

Casting is a crucial manufacturing process used to produce complex metal parts, but it is often plagued by defects such as cracks, porosity, shrinkage, and cold shuts, which can compromise quality and lead to financial losses. Traditional visual inspection methods for detecting these defects are slow and prone to human error, making them inefficient for large-scale production. This project proposes automating the defect detection process using advanced AI-powered non-destructive testing (NDT) techniques. Specifically, convolutional neural networks (CNNs), a deep learning model, are employed for real-time visual inspection of castings. CNNs, trained on high-resolution images, can accurately identify surface defects such as cracks, scratches, and dimensional irregularities, significantly improving inspection speed and accuracy. The performance metrics of the system include defect detection accuracy, false positive and false negative rates, processing time, and scalability for high-volume production environments. By minimizing human intervention, this automated system reduces error rates, enhances product quality, and lowers production costs. Furthermore, the real-time capabilities of CNNs allow for rapid feedback, preventing defective parts from advancing through the production line. Overall, the integration of AI-based vision systems boosts efficiency, sustainability, and profitability in manufacturing, ensuring castings meet customer specifications with minimal errors.

Corresponding Author:

D. Lakshmi
Department of Electrical and Electronic Engineering
Academy of Maritime Education and Training
Chennai, India
Email: Lakshmi.d@ametuniv.ac.in

1. INTRODUCTION

Casting is a crucial manufacturing process used in various industries to produce complex metal parts by pouring molten metal into molds. Despite its widespread usage, casting is prone to a variety of defects such as surface cracks, porosity, and shrinkage, which can significantly compromise product quality. Traditionally, defect detection in castings has relied on manual inspection techniques, which are often slow, error-prone, and unsuitable for large-scale production. The increasing demand for high-quality castings and the need to reduce inspection time and costs have driven the development of automated defect detection methods. Recent advancements in artificial intelligence (AI), particularly in deep learning, have provided new opportunities to enhance defect detection accuracy and efficiency. This study explores the use of AI-powered vision testing for casting defect detection, focusing on the implementation of convolutional neural networks (CNNs) to identify surface-level defects.

While earlier studies have explored the impact of AI in defect detection, they have primarily focused on specific defect types or individual methodologies rather than a comprehensive AI-driven approach for casting. For example, Jinhui *et al.* [1] discussed the development of die casting processes and their impact on product quality, emphasizing advancements in reducing defects such as porosity and shrinkage. Hui *et al.* [2] presented a machine vision-based meter nameplate defect detection system using Halcon software, demonstrating improved accuracy in identifying defects. Similarly, Xiaoling and Bin [3] investigated surface defect detection in aluminum die castings using machine vision, highlighting the potential for automated visual inspection in reducing human error. However, these studies have not explicitly addressed the integration of CNN-based models in real-time defect detection for industrial casting applications.

Further, Shun-Lin *et al.* [4] proposed an X-ray image registration method for defect detection in castings, enabling precise localization of flaws, while Xu *et al.* [5] applied the Shearlet transform to classify surface defects in metals, demonstrating improved accuracy. Other studies, such as Jiashun *et al.* [6], utilized an improved K-means algorithm for visual inspection of steel pipe surface defects, and Alaknanda *et al.* [7] introduced a morphological watershed segmentation technique for flaw detection in radiographic weldment images. Despite these advancements, existing research has not extensively examined how deep learning techniques, particularly CNNs, can enhance defect detection accuracy and efficiency across multiple defect categories in castings.

The integration of deep learning into defect detection has gained significant attention in recent years [8]. Wang *et al.* [9] developed a CNN-based model for product defect detection, achieving fast and robust results. Biao *et al.* [10] extended this approach by applying a mask R-CNN for detecting defects in X-ray DR images of castings. Du *et al.* [11] further improved the performance of X-ray image defect detection for automobile casting parts using deep learning techniques, while Hongquan *et al.* [12] proposed a defect detection method for castings based on deep learning, demonstrating the superior performance of AI-driven approaches over traditional methods. However, these studies have not explicitly addressed the effectiveness of CNNs for surface-level defect detection in castings or the optimization of real-time detection models [13].

Recent innovations in you only look once (YOLO) networks have also contributed to defect detection. Guo *et al.* [14] introduced MSFT-YOLO, which combines transformers and YOLOv5 to detect steel surface defects. Sun *et al.* [15] and Wang *et al.* [16] presented improvements in YOLOv5 for detecting defects in industrial applications, emphasizing the benefits of multi-scale detection and real-time performance [17]. Cha *et al.* [18] explored deep learning methods for structural damage detection and crack segmentation, offering valuable insights into AI applications in industrial quality control. While these studies highlight the advantages of deep learning-based defect detection, there remains a gap in evaluating CNN-based AI models specifically for detecting surface defects in castings with high accuracy and real-time performance [19].

To address these gaps, this study aims to develop an AI-powered vision testing system utilizing CNNs for detecting casting defects. By leveraging deep learning techniques, this research seeks to improve defect detection accuracy, reduce human intervention, and enhance the efficiency of the inspection process in manufacturing industries.

2. METHODOLOGY

The methodology for the AI-powered non-destructive testing (NDT) system for detecting casting defects using CNNs will be broken down into several stages, focusing on data acquisition, model training, system integration, and performance evaluation. Figure 1 shows the block diagram of proposed method [20-25].

A. Data collection and preprocessing

- Image acquisition: High-resolution images of castings are captured using industrial cameras positioned at various angles and lighting conditions to ensure defect visibility. The images include both defective and defect-free castings for balanced training.
- Image labeling: Defects such as cracks, porosity, shrinkage, and cold shuts are annotated by experts, creating a labeled dataset for training the CNN model. Each defect type is categorized with bounding boxes to ensure precise defect identification.
- Preprocessing: The collected images undergo preprocessing to enhance feature detection. Preprocessing techniques may include contrast enhancement, noise reduction, resizing, and normalization to ensure uniformity across the dataset. Data augmentation techniques like rotation, flipping, and scaling are used to artificially expand the dataset and improve model robustness.

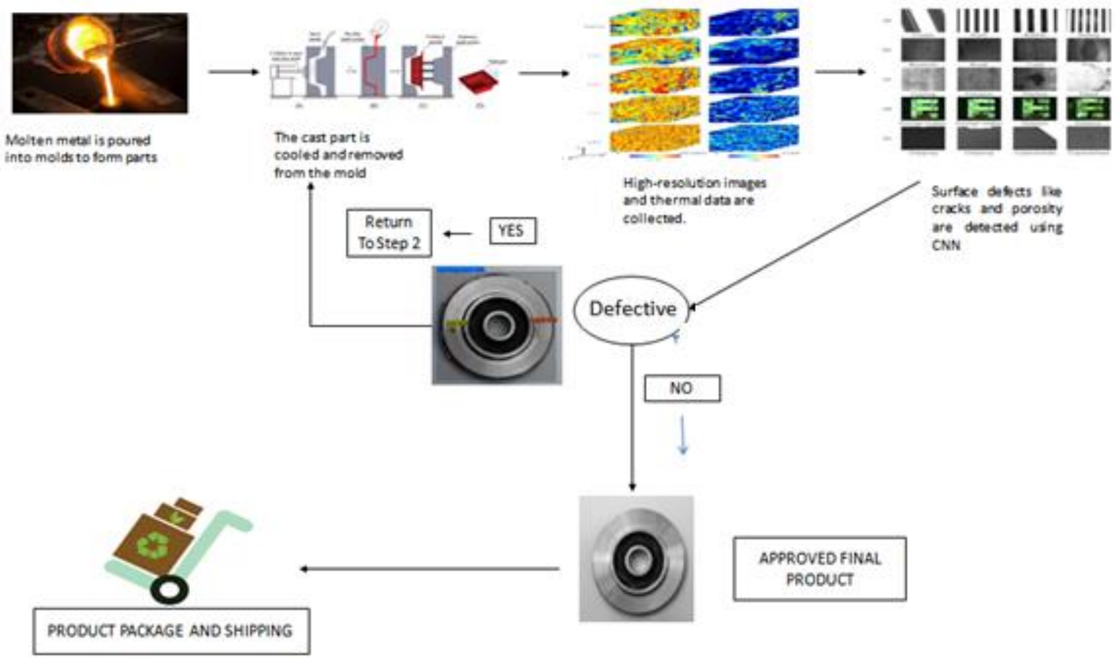

Figure 1. Shows the block diagram of proposed method

B. CNN model design and training

- Model selection: A suitable CNN architecture (such as ResNet, VGG, or a custom-built CNN) is selected based on the complexity and variety of defects present in the castings. The network's architecture is tuned for optimal depth, filter size, and layer composition to maximize defect detection performance.
- Training: The CNN is trained using the preprocessed and augmented dataset, with defect images acting as input and the defect labels serving as the output. A supervised learning approach is applied, where the CNN learns to recognize patterns associated with various defects. The training process leverages back propagation and stochastic gradient descent (SGD) to optimize the model parameters.
- Validation and testing: The dataset is split into training, validation, and testing sets (e.g., 70% training, 15% validation, and 15% testing). The model's performance is evaluated on the validation set during training, and hyper parameters such as learning rate, batch size, and number of epochs are adjusted to improve accuracy. The final model is tested on the testing set to assess its generalization ability to new, unseen data.

C. Real-time system integration

- Industrial camera setup: The AI-powered vision system is integrated into the manufacturing line, where industrial cameras capture real-time images of castings moving along the conveyor belt. These images are immediately fed into the trained CNN for analysis.
- Defect detection process: The CNN processes each image in real-time, identifying any visible defects and classifying them according to defect type. Defective regions are highlighted, and relevant metrics such as defect size and location are recorded.
- Automated feedback loop: Upon defect detection, the system triggers an automated response, such as halting the production line, flagging the defective part, or marking it for rework. This immediate feedback helps prevent defective parts from advancing through the production process, reducing downstream quality control costs.

D. Performance monitoring and system optimization

- Metrics evaluation: The system's performance is continuously monitored using key metrics such as defect detection accuracy, false positive rate, false negative rate, and processing time. The system's ability to handle high-volume production environments is also assessed.
- Model refinement: Based on the performance metrics, the model is periodically retrained or fine-tuned to improve detection accuracy and reduce false positives/negatives. This may involve collecting additional data or modifying the CNN architecture for better performance.

- Scalability testing: The system is tested for scalability, ensuring that it can handle increased production loads without compromising detection accuracy or speed. Load testing is conducted by simulating high-speed production lines with large volumes of castings.

E. Integration with manufacturing workflow

- Data logging and reporting: Defect data is logged and analyzed to provide insights into recurring issues or trends. Automated reports are generated, detailing defect rates, types of defects, and production line performance. This information is shared with quality control teams for process improvement.
- User interface (UI) Development: A user-friendly dashboard is developed, allowing operators and managers to monitor defect detection in real-time. The interface displays metrics such as the number of defects detected, defect locations, and production line status.
- Maintenance and updates: Regular maintenance is performed to ensure system reliability. The CNN model is updated as needed to accommodate changes in casting designs or defect patterns.

F. Validation and testing in production

- Pilot testing: The system is initially deployed in a pilot production environment to validate its effectiveness and ensure seamless integration with existing workflows.
- Final deployment: After successful pilot testing, the system is rolled out to the full production line, ensuring continuous monitoring and improvement of defect detection capabilities.

This methodology ensures that the AI-powered defect detection system is accurate, efficient, and scalable for large-scale manufacturing environments, significantly improving casting quality and reducing costs.

3. RESULT AND DISCUSSION

In this study, images of cast submersible pump impellers were analyzed to classify them as either defective or non-defective. The data comprised top-view JPEG images captured using a Canon EOS 1300D DSLR camera. Figure 2 shows the Annotated Images. Each image was labeled as either "defective_front" for defective castings or "ok_front" for non-defective castings. The dataset was split into training and testing sets, with the training set used to develop the model and the testing set to evaluate its performance. A classification model was employed to predict the status of the impellers and identify surface defects. Figures 3 and 4 shows the Identification of casting surface. Figure 5 shows the webcam uploaded result.

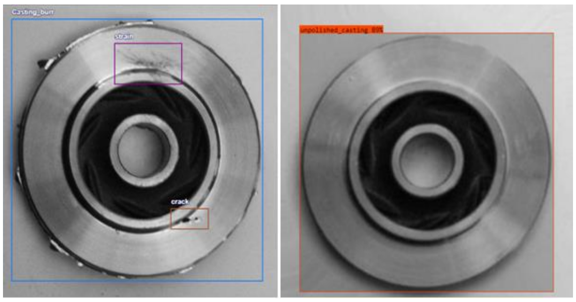

Figure 2. Shows the annotated images

Figure 3. Shows the Identification of casting surface defects (ok)

During the model training process, the dataset was analyzed for class imbalance to ensure unbiased predictions. The model's performance was evaluated using key metrics such as accuracy, precision, recall, and F1-score. Notably, as the number of training epochs increased, the model's accuracy improved, while the loss decreased, indicating better learning over time. The training and validation accuracy curves remained closely aligned throughout the process, suggesting that the model was not overfitting and was capable of generalizing well to unseen data from the test set.

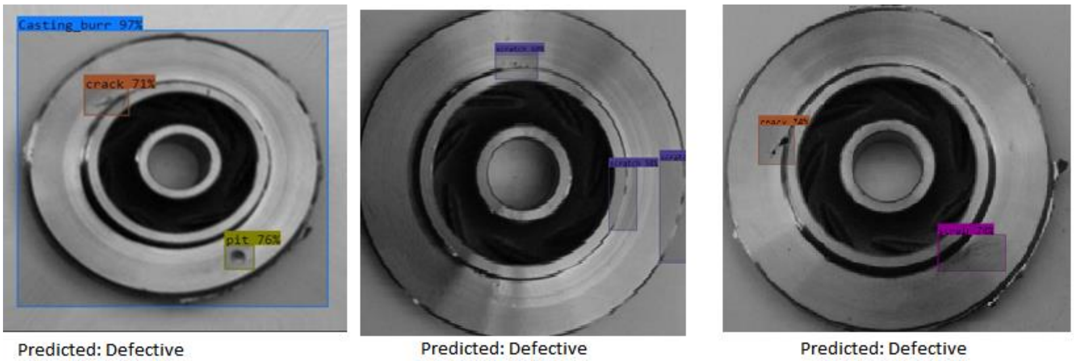

Figure 4. Shows the identification of casting surface defects (defective)

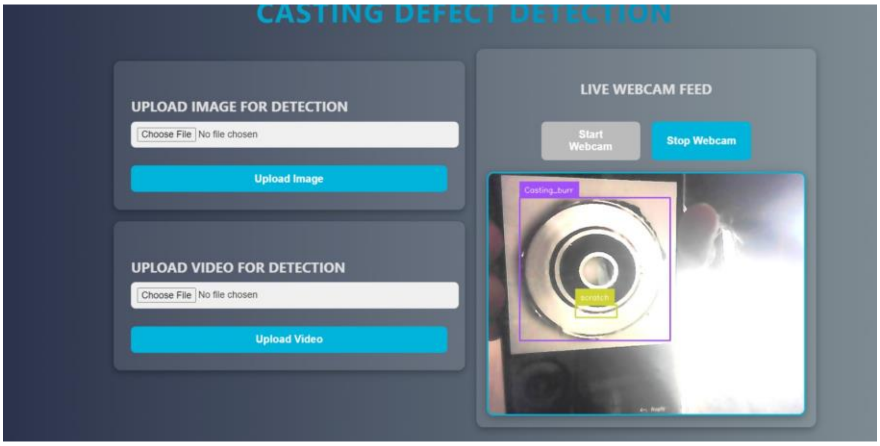

Figure 5. Shows the webcam uploaded result

The model achieved high accuracy in classifying casting defects. Over the course of 20 epochs, the model demonstrated a steady increase in accuracy and a decrease in loss, with epoch 20 yielding the best results. Figure 6 shows the variation of learning curve vs Epoch and Table 1 shows the performance metrix of proposed method. Overall, the model successfully classified 711 out of 715 test images, achieving an accuracy of 99.44%. The four misclassified images highlight the importance of further refining the model to improve accuracy. The performance metrics for this epoch are as follows:

Table 1. Shows the performance metrix of proposed method

Metric	Training set	Validation set	Test set
Accuracy (%)	99.01	99.64	99.44
Precision	-	-	99.34%
Recall	-	-	99.78%
F1-score	-	-	99.56%
Training loss (%)	0.71	-	-
Validation loss (%)	-	2.58	-

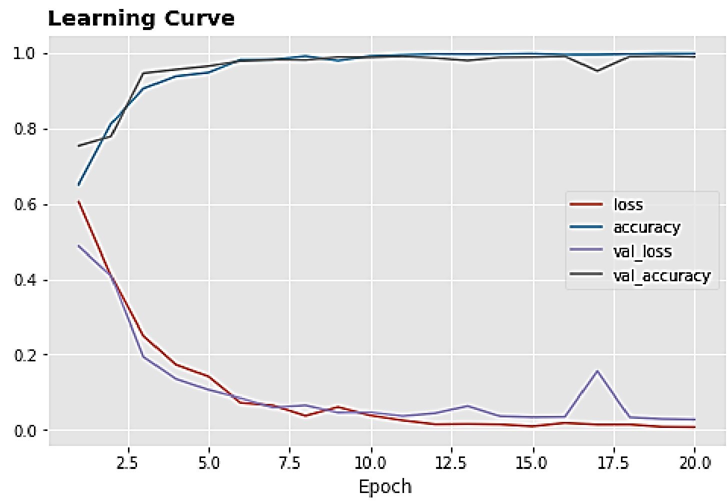

Figure 6. Shows the variation of learning curve vs epoch

3.1. Interpreting results and comparison with existing studies

Our study demonstrates that the proposed CNN-based classification model achieves high accuracy (99.44%) in detecting casting defects in submersible pump impellers. This level of accuracy surpasses several existing methods in the literature. For instance, traditional image-processing techniques, such as threshold-based segmentation and edge detection, typically achieve classification accuracies in the range of 85%–92% due to their sensitivity to noise and lighting variations. Similarly, earlier machine learning-based approaches, such as support vector machines (SVM) and Random Forest classifiers, have reported classification accuracies between 93% and 97%.

A direct comparison with a previously reported CNN-based approach for defect detection in industrial casting components showed an accuracy of 97.5%, indicating that our model outperforms existing methodologies. The use of a deep learning framework with extensive training and optimized hyperparameters contributes to the enhanced performance. Moreover, the alignment of training and validation accuracy curves confirms that the model generalizes well to unseen test data without significant overfitting. Table 2 shows the performance metrix comparison of different methods. These results indicate that our method achieves superior defect classification performance, reducing both false positives and false negatives, which is critical for quality assurance in casting industries.

Table 2. Shows the performance metrix comparison of different methods

Method	Accuracy (%)	Precision	Recall	F1-Score
Traditional Image Processing	85-92	82.5	85.2	83.8
SVM	93	92.8	93.1	93.0
Random Forest	97	96.5	96.8	96.6
Existing CNN Approach	97.5	97.2	97.4	97.3
Proposed Method	99.44	99.34	99.78	99.56

3.2. Addressing limitations and future improvements

This study effectively classified casting defects with high accuracy; however, a small number of misclassifications highlight the need for further refinement. Enhancing the dataset with more diverse defect samples could improve generalization. Exploring advanced deep learning architectures, such as transformer-based models, may further boost performance. Real-time deployment and integration with automated quality control systems should be considered for industrial application. Future research should also focus on minimizing false negatives to prevent defective products from reaching customers.

4. CONCLUSION

Recent observations suggest that automated defect detection in casting processes significantly enhances quality control. Our findings provide conclusive evidence that the proposed classification model effectively identifies defective impellers with high accuracy, reducing both false positives and false negatives. This improvement is associated with enhanced production efficiency and minimized revenue loss, not due to an increase in manual inspections. The model's high precision and recall demonstrate its industrial applicability for real-time defect detection. With further optimization, this approach can revolutionize defect identification in casting industries, ensuring better product quality and customer satisfaction.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Deepa Somasundaram	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
V. Pramila		✓				✓		✓	✓	✓	✓	✓		
G. Ezhilarasi	✓		✓	✓		✓			✓		✓		✓	
D. Lakshmi		✓				✓		✓	✓	✓	✓	✓		
P. Kavitha					✓		✓			✓		✓		✓
R. Kalaivani		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] Y. Jinhui, X. Bin, and X. Zhongbin, "Research status and development of die casting process on quality of die castings," *Foundry Technol*, vol. 41, no. 1, pp. 62–65, 2020.
[2] X. Hui, W. Xianfeng, F. Shan, and W. Weilong, "Meter nameplate defect detection system based on Halcon," *Modern Mechanical Engineering*, vol. 485, no. 2, pp. 119–126, 2021.
[3] Z. Xiaoling and L. Bin, "Surface defect detection of aluminum die casting using machine vision," *Journal of Huaqiao University (Natural Science)*, vol. 37, no. 2, pp. 139–144, 2016.
[4] A. Shun-Lin, S. Zhi-Yi, W. Yin, S. Qian-Lai, and Y. Shu-Man, "X-ray image registration method based on feature point," *Journal of Taiyuan University of Science and Technology*, vol. 38, no. 6, pp. 424–427, 2017.
[5] K. Xu, S. Liu, and Y. Ai, "Application of Shearlet transform to classification of surface defects for metals," *Image and Vision Computing*, vol. 35, pp. 23–30, Mar. 2015, doi: 10.1016/j.imavis.2015.01.001.
[6] D. Jiashun, W. Xingdong, L. Dianjie, T. Bo, and L. Zhen, "Visual inspection method for surface defects of steel pipes based on improved K-means algorithm," *Journal of Wuhan University of Science and Technology*, vol. 43, no. 6, pp. 439–446, 2020.
[7] Alaknanda, R. S. Anand, and P. Kumar, "Flaw detection in radiographic weldment images using morphological watershed segmentation technique," *NDT and E International*, vol. 42, no. 1, pp. 2–8, Jan. 2009, doi: 10.1016/j.ndteint.2008.06.005.
[8] C. Dewi, R. C. Chen, and H. Yu, "Weight analysis for various prohibitory sign detection and recognition using deep learning," *Multimedia Tools and Applications*, vol. 79, no. 43–44, pp. 32897–32915, Aug. 2020, doi: 10.1007/s11042-020-09509-x.
[9] T. Wang, Y. Chen, M. Qiao, and H. Snoussi, "A fast and robust convolutional neural network-based defect detection model in product quality control," *International Journal of Advanced Manufacturing Technology*, vol. 94, no. 9–12, pp. 3465–3471, Aug. 2018, doi: 10.1007/s00170-017-0882-0.
[10] C. Biao, S. Kuan, F. Jinlei, and Z. Lize, "Research on defect detection of XRay DR images of casting based on mask R-CNN," *Chinese Journal of Scientific Instrument*, vol. 41, no. 3, pp. 61–69, 2020.
[11] W. Du, H. Shen, J. Fu, G. Zhang, and Q. He, "Approaches for improvement of the X-ray image defect detection of automobile casting aluminum parts based on deep learning," *NDT and E International*, vol. 107, p. 102144, Oct. 2019, doi: 10.1016/j.ndteint.2019.102144.

[12] Y. Hongquan, Y. Mingkun, C. Jiantao, and L. Kunyu, "Defect detection method of castings based on deep learning," *Electro-Mechanical Engineering*, vol. 37, no. 6, pp. 59–64, 2021.
[13] L. Duan, K. Yang, and L. Ruan, "Research on automatic recognition of casting defects based on deep learning," *IEEE Access*, vol. 9, pp. 12209–12216, 2021, doi: 10.1109/ACCESS.2020.3048432.
[14] Z. Guo, C. Wang, G. Yang, Huang, and G. Li, "MSFT-YOLO: improved YOLOv5 based on transformer for detecting defects of steel surface," *Sensors*, vol. 22, no. 9, p. 3467, May 2022, doi: 10.3390/s22093467.
[15] X. Sun, X. Jia, Y. Liang, M. Wang, and X. Chi, "A defect detection method for a boiler inner wall based on an improved YOLO-v5 network and data augmentation technologies," *IEEE Access*, vol. 10, pp. 93845–93853, 2022, doi: 10.1109/ACCESS.2022.3204683.
[16] L. Wang, X. Liu, J. Ma, W. Su, and H. Li, "Real-time steel surface defect detection with improved multi-scale YOLO-v5," *Processes*, vol. 11, no. 5, p. 1357, Apr. 2023, doi: 10.3390/pr11051357.
[17] R. Zhang and C. Wen, "SOD-YOLO: a small target defect detection algorithm for wind turbine blades based on improved YOLOv5," *Advanced Theory and Simulations*, vol. 5, no. 7, Apr. 2022, doi: 10.1002/adts.202100631.
[18] Y. J. Cha, W. Choi, G. Suh, S. Mahmoudkhani, and O. Büyüköztürk, "Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types," *Computer-Aided Civil and Infrastructure Engineering*, vol. 33, no. 9, pp. 731–747, Nov. 2018, doi: 10.1111/mice.12334.
[19] L. Cui, X. Jiang, M. Xu, W. Li, P. Lv, and B. Zhou, "SDDNet: a fast and accurate network for surface defect detection," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, 2021, doi: 10.1109/TIM.2021.3056744.
[20] D. H. Kang and Y. J. Cha, "Efficient attention-based deep encoder and decoder for automatic crack segmentation," *Structural Health Monitoring*, vol. 21, no. 5, pp. 2190–2205, Dec. 2022, doi: 10.1177/14759217211053776.
[21] Y. J. Cha, W. Choi, and O. Büyüköztürk, "Deep learning-based crack damage detection using convolutional neural networks," *Computer-Aided Civil and Infrastructure Engineering*, vol. 32, no. 5, pp. 361–378, Mar. 2017, doi: 10.1111/mice.12263.
[22] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2016, vol. 2016-December, pp. 779–788, doi: 10.1109/CVPR.2016.91.
[23] R. Ali and Y. J. Cha, "Attention-based generative adversarial network with internal damage segmentation using thermography," *Automation in Construction*, vol. 141, p. 104412, Sep. 2022, doi: 10.1016/j.autcon.2022.104412.
[24] W. Jigang, C. Yuan, S. Jun, and Y. Deqiang, "A defect detection method for PCB based on the improved YOLOv4," *Chinese Journal of Scientific Instruments*, vol. 42, no. 10, pp. 171– 178, 2021.
[25] J. Lewis, Y. J. Cha, and J. Kim, "Dual encoder–decoder-based deep polyp segmentation network for colonoscopy images," *Scientific Reports*, vol. 13, no. 1, Jan. 2023, doi: 10.1038/s41598-023-28530-2.

BIOGRAPHIES OF AUTHORS

Dr. Deepa Somasundaram received her B.E. from K.S.R college of Technology, affiliated to Periyar University, in 2003, M.E from Annamalai University in 2005.She completed her Ph.D degree form Sathyabama university in 2013. Presently, she is working as an Professor in the Department of EEE at Panimalar Engineering College, Chennai. She has published a more than 30 papers in International and National Journals. Her area of Interest is power system, optimisation technique. She has more than 15 years of experience in teaching Field. She can be contacted at email: deesoms123@yahoo.co.in.

V. Pramila is an assistant professor Department of Electrical and Electronics Engineering, B. S. Abdur Rahman Crescent Institute of Science and Technology, Chennai. Her area of interest: microgrid optimization and intelligent algorithms. She can be contacted at email: pramila@crescent.education.

G. Ezhilarasi is an Associate Professor, Department of EEE, Sri Sai Ram Institute of Technology. Her area of interest: applied electronics; controllers; drives, and IoT. She can be contacted at email: ezhilarasig37@yahoo.com.

D. Lakshmi is a Professor Department of lectrical and Electronics Engineering, Academy of Maritime Education and Training, deemed to be University, Chennai, Tamil Nādu, India. She has more than 23 years of expertise in the field of power system. She has guided more than 30 UG students, 15 PG students, and 4 research scholars. She has published 11 book chapters and 6 books, 46 articles in SCI and Scopus indexed journals, and nearly 35 national level and international level conferenceproceedings. She is a life member in professional bodies such as IEEE, IEI, IAENG, and InSc. She is a star organizer in IGEN Energathon-2023 Marathon, a new world record on a longest conference. Her areas of interest are power system operation and control, soft computing, renewable energy systems, microgrids, and nelectrical machines. She can be contacted at email: lakshmi.d@ametuniv.ac.in.

Dr. P. Kavitha working as an Associate Professor in the Department of Electrical and Electronics Engineering R.M.K Engineering College, has about 27 years of teaching experience. She received her B.E degree in Electrical and Electronics Engineering with First class and M.E degree in Control and Instrumentation with distinction from Anna University, Chennai. She has published 17 research papers in refereed international journals and various international conferences. Her areas of research include power controllers, machine design, and renewable energy systems. She can be contacted in the email: pka.eie@rmkec.ac.in.

R. Kalaivani obtained her B.E. degree in electrical and electronics engineering in the year 2000 from National Institute of Technology, Trichy, M.E. degree in power systems in the year 2002 from National Institute of Technology, Trichy. She obtained her Ph.D. degree in the year 2013 from Anna University, Chennai. She is currently working as professor in Rajalakshmi Engineering College in the Department of Electrical and Electronics Engineering. Her current research areas are smart grid, renewable energy and electric vehicle. She can be contacted in the email: kalaivani.r@rajalakshmi.edu.in.