1. Introduction

Accurate and systematical examinations of fracture surfaces are important for understanding the damage mechanism. In fracture science, materials’ failure behavior is often identified as ductile fracture, brittle fracture, and fatigue fracture. Furthermore, materials exposed to harmful environments often suffer from an environment-assisted fracture, e.g., corrosion fracture. As the important feature of a fracture surface, fracture initiation site is often investigated to reveal the fracture mechanisms. However, the human-effort-based characterizations easily miss some hard-to-detected features with human eye and involve lots of labor force. In this study, computer-aided detection of fracture initiation sites is proposed to augment human expertise to efficiently find the fracture initiation sites, and thus to reduce the labor cost. With a deep-learning you only look once object detector, the fracture initiation sites of steel were successfully detected in this study. Furthermore, based on the trained detection model, an easy-to-use application for detecting initiation sites has been further developed, exhibiting great potential for high-efficiency detection of fracture initiation sites.

KEY WORDS: fracture initiation sites; high-efficiency detection; deep learning; you only look once.

2. YOLO Training

Most detection approaches like region-convolutional neural network use region proposal methods to first generate potential bounding boxes in an image and then classify, refine, and rescore the boxes to detect an object. With the penetration of deep learning technology into various domains, deep learning is increasingly applied to characterize microstructural features in materials science. For a certain application, careful selection and evaluation of a technique are critical to achieve the desired results because the practical application has to balance the trained model’s accuracy, analysis speed, and simplicity. A systematic investigation of the deep-learning-based techniques has demonstrated that a you only look once (YOLO) technique has the fastest detection speed with maintaining a satisfactory accuracy, which enables a real-time detection. Consequently, given the satisfactory performance of YOLO technique on object detection, YOLO was employed to detect the fracture initiation sites in this study, so as to assist the human-effort identification. Here, brittle fracture initiation sites were used as the study target. Investigations of the effect of dataset size and dynamic detection of multiple initiation sites were conducted to identify the detection performance of YOLO on fracture initiation sites. Furthermore, based on the trained detection model, an easy-to-use application for identifying the fracture initiation sites was further tried to develop.
convolutional network to simultaneously predict multiple bounding boxes and class probabilities for those boxes.\textsuperscript{14) YOLO technique has evolved five versions from YOLOv1 to YOLOv5\textsuperscript{14–18) until now. It should be pointed out that YOLOv4 and YOLOv5 have not come out when this study started. Thus, YOLOv3\textsuperscript{16) was employed to conduct the detection task in this study.}

Before training a detection model to detect an unknown object from an existing database, it is necessary to label the relevant features of the desired object with some human effort. In this study, the empirical features of river pattern\textsuperscript{19,20) were labeled in advance tracking with the brittle fracture initiation sites. Figure 1 illustrates feature labeling for a specific fracture initiation point using a rectangular bounding box. Because the fracture facets vary in size and morphology, each training image’s attributes were meticulously labeled. The labeling method allocated an address to each pixel in the image, and then recorded the bounding box coordinates (center x, center y, width, height). As a result, by reading the recorded addresses, the training process could follow the fracture initiation sites.

3. Image Datasets

In this study, in-house experimentally observed scanning electron microscopy images regarding fracture surfaces were used as training and testing data. For 206 steel grades in which the weld heat affected zone of the thick plate was simulated by thermal cycle test, a full size (10×10 (mm)) Charpy impact test was carried out, and one fractured surface with high brittle fracture fraction was selected. A fracture surface image was captured so that 2 mm-V notch was located at the upper side of the image. The magnification was 4 levels from a low magnification of ×30 (actual field of view: 3.2 × 4.3 (mm) and pixel size: 960 × width 1 280) to ×100, ×200, and ×500, and a total of 900 input images were subjected to YOLO analysis. To evaluate the detection performance of the trained models, four training datasets (T1, T2, T3, and T4) containing images of various numbers and magnifications were created (Table 1). All images with magnification ranging from ×30 up to ×500 were simultaneously input to train the YOLO model. In ground truth images only a fracture initiation site was suggested, and other characteristic features such as a river pattern were not apparently used for labelling. The trained models were put to the test using a dataset of 300 unlabeled images (Test).

4. Detection Performance YOLO on Fracture Initiation Sites

Figure 2 show the detection rate of models trained with different datasets. Unsurprisingly, the detection rate presented an increasing tendency with increasing the dataset size for any image magnification, as shown in Fig. 2(a). However, the detection rate appeared to be irregular with changing magnification rather than being higher at higher magnification as expected, as indicated by model T1. Nevertheless, as shown in Fig. 2(b), the detection rate averaged by different magnifications of the trained models still showed an increasing tendency with increasing the dataset

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<th>Dataset</th>
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![Fig. 2.](image)

(a) Detection rate of models trained with different datasets under different image magnifications and (b) averaged detection rate of trained models.
size. Evenly, the detection rate was greater than 95% for the present testing data when the training images reached a number of 300 (T3).

The detection confidence level of the initiation sites was also investigated here. Figure 3 shows the results of different models for a certain testing image (200×). The results demonstrate that, in addition to improving detection rate, a larger training dataset size could also enhance the detection confidence level, as indicated by the number attached to bounding box. Notably, when the confidence level reaches 0.1, it is defined as a successful detection case.

Figure 4 shows the detection confidence level of different magnifications tested by the model T4. The result demonstrates that a higher magnification readily captured the fracture initiation site with a higher confidence level, although the influence of magnification on the detection rate is fluctuant (Fig. 2(a)). In other words, a larger observed fracture facet size could provide a clearer river pattern of the fracture initiation site and thus improve its detection confidence.

More training data and a larger fracture facet with a clearer river pattern, according to the preceding findings, improve the trained model’s detection performance. However, sometimes things easily turn into their opposite when

![Fig. 3. Detection confidence of the different models of (a) T1, (b) T2, (c) T3, and T4.](image)

![Fig. 4. Detection confidence of different magnifications of (a) 30×, (b) 100×, (c) 200×, and (d) 500×.](image)
they become extreme. Figure 5 shows some detection failure cases for the high-magnification images (500×) (left column) tested by model T4. As a comparison, the results under their corresponding lower magnification (200×) are also provided (right column). It clearly shows that the higher-magnification images failed to identify the fracture initiation sites. By carefully observing the fracture facets, these failures are probably attributed to the uncompleted river pattern under a much higher magnification, which caused trouble in identifying the fracture initiation site during testing.

Detection performance of multiple initiation sites was further evaluated. Figure 6 illustrates the testing result using the trained model T4 for a testing image combined by four independent fracture images (30×). The result exhibited that multiple sites were successfully identified in spite of relatively low confidence level. Furthermore, the multiple sites were also successfully identified under a dynamic test, as shown in Animation S1 (Supplementary Material), which suggests great potential of YOLO on the high-efficiency detection of fracture initiation sites.

Based on the achieved results, an easy-to-use application for detecting the fracture initiation sites has been developed.

Fig. 5. Detection failure cases under high magnification (a and c) and successful cases under their corresponding low magnification (b and d).

Fig. 6. Multi-site detection result using model T4.
5. Summary

With the prospect of high-efficiency detection of fracture initiation sites, a computer-aided strategy is proposed to identify fracture initiation sites with a YOLO object detector in this study. The investigations regarding the influences of the training dataset size, magnification of fracture images, multiple-site case, and dynamic test on the detection performance exhibit great potential of YOLO on the high-efficiency detection of fracture initiation sites. Furthermore, based on the achieved results, an easy-to-use application has been developed for detecting fracture initiation sites.

Supporting Information

Dynamic detection of fracture initiation sites is demonstrated in the supporting movie.

This material is available on the Journal website at https://doi.org/10.2355/isijinternational.ISIJINT-2022-105.

Declaration of Competing Interest

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence this work.

Acknowledgements

The authors would like to thank the Nippon Steel advanced research collaborative project for the support of the raw data.

REFERENCES