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Semantic segmentation for the analysis of creep voids in metallic materials

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Introduction

- High-temperature metallic materials suffer from creep due to mechanical stresses
- Prolonged creep condition causes material deformation and component failure (Fig. 1)
- Formation of creep voids in material structure is a prime indication of creep phenomenon
- Timely & accurate detection of creep voids helps in better life cycle management of valuable products
- Semantic image segmentation reduces human errors and speeds up the analysis process

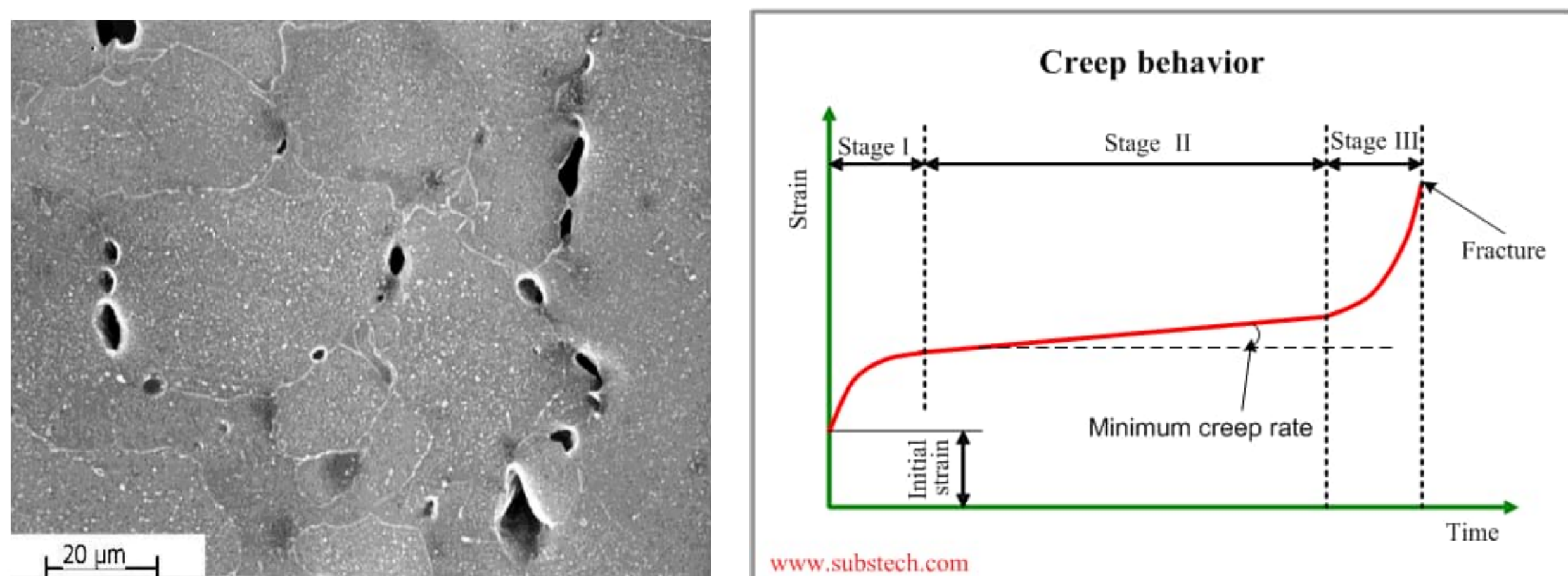


Fig. 1. Creep voids in materials and different stages of creep behavior

Semantic image segmentation

- Assigning a class or label to every pixel of the image
- Information about the location, size, and shape of objects
- Several applications including medical imaging, object detection, and recognition tasks
- Segmentation models generally consist of an encoder network followed by a decoder network
- Encoder is usually a pre-trained classification network, such as VGG or ResNet
- Decoder projects the discriminative features learned by the encoder into the pixel space, performing classification

Case study – creep voids in copper samples

- SEM images of oxygen-free phosphorous-doped copper sample surfaces
- Our task is to distinguish creep voids (white pixels) from the normal surface (black pixels) (Fig. 2)
- DeepLab-v3+ [2] model built on top of CNN architecture with ResNet encoder pre-trained on ImageNet dataset
- Model training 251 (70%), validation 54 (15%), and testing 55 (15%) images
- PyTorch-based Segmentation Models [1] library and the Google Colab environment for model implementation

[1] Yakubovskiy, P. 2022. Segmentation Models. Online: <https://smp.readthedocs.io/en/latest/index.html>
 [2] Chen, L.C., Zhu, Y. 2018. Semantic Image Segmentation with DeepLab in TensorFlow. Google AI Blog. Available at: <https://ai.googleblog.com/2018/03/semantic-image-segmentation-with.html>

Model performance

- Training time about 17 minutes (wall time) for 200 epochs
- Testing IoU score of 0.994 and dice loss of 0.003
- Good agreement between model prediction and ground truth (Fig. 2)
- Information about area fraction (Fig. 3) and number of creep voids in an image (Fig. 4).

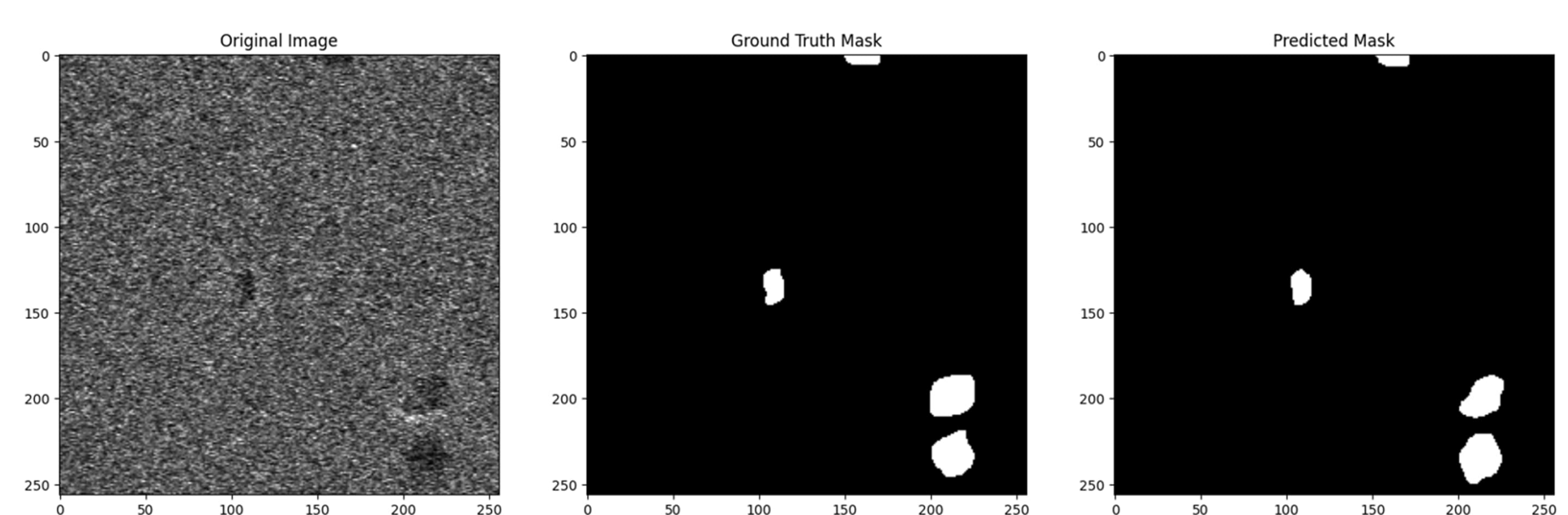


Fig. 2. Comparison between ground truth and predicted masks

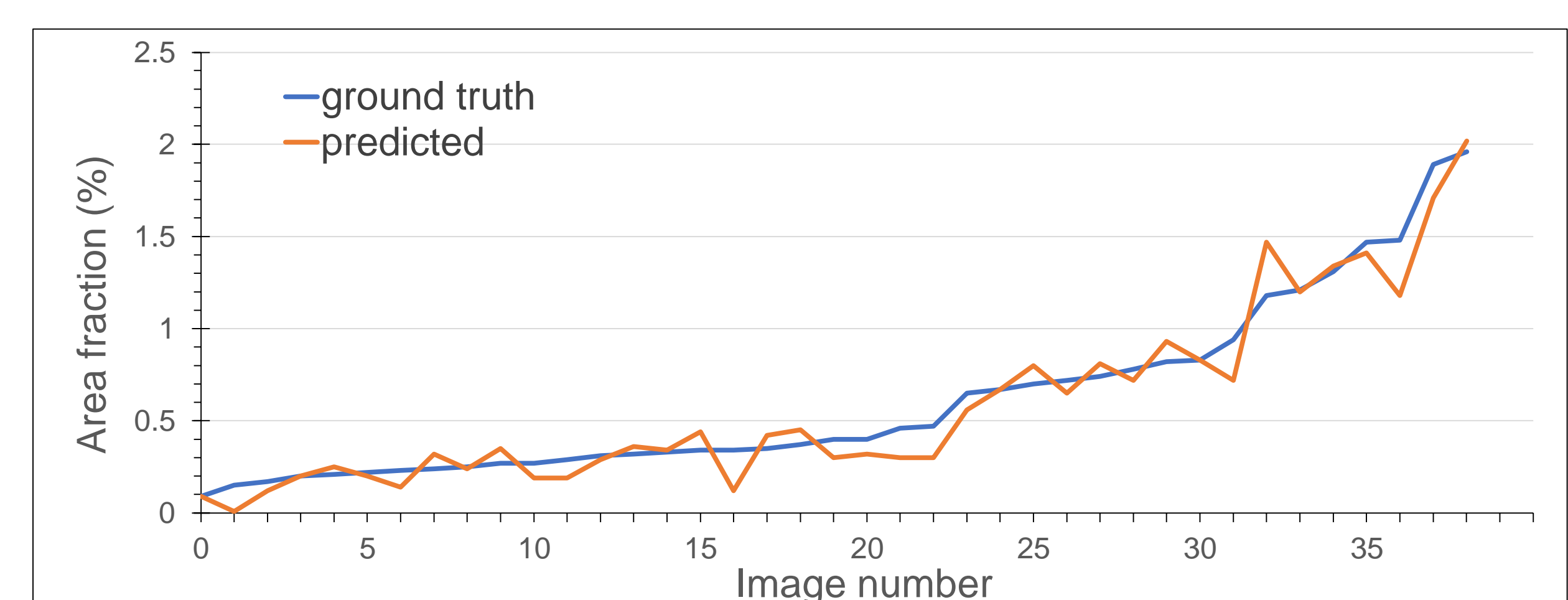


Fig. 3. Area fraction of creep voids, ground truth vs. predicted

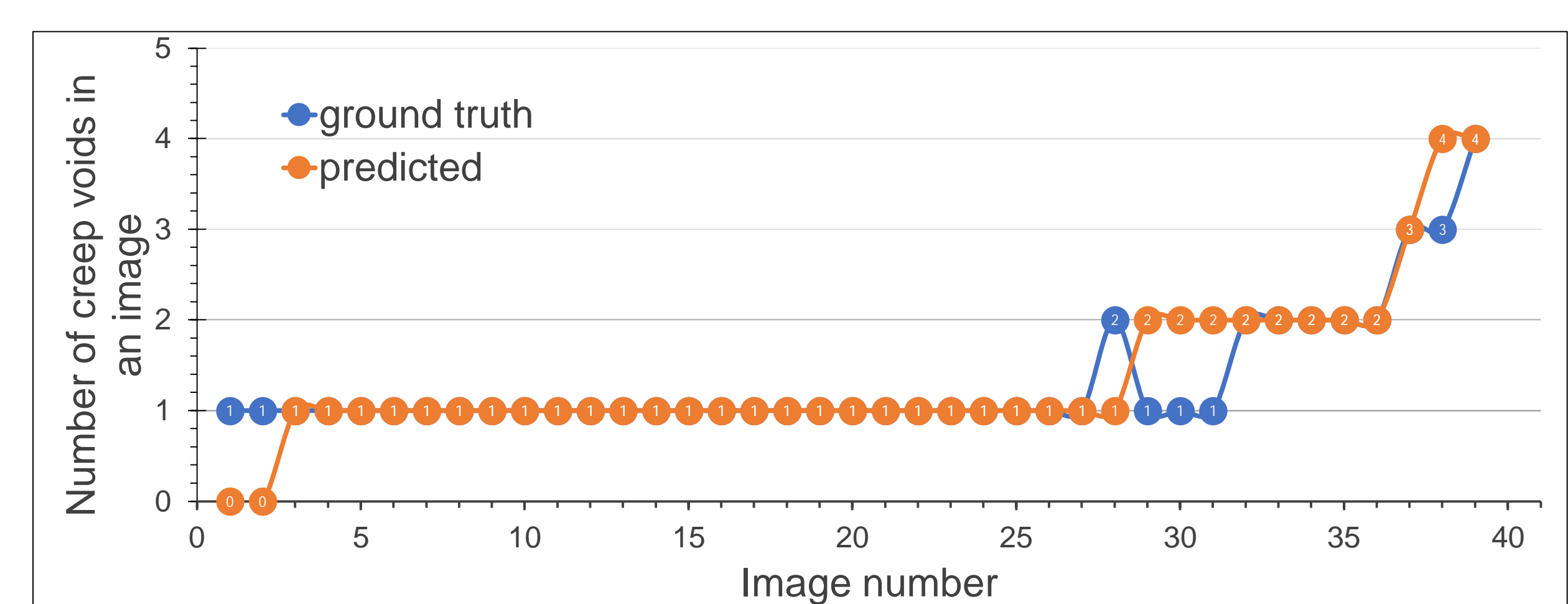


Fig. 4. Number of creep voids in an image, ground truth vs. predicted

Conclusion

- Timely and reliable detection of creep voids is vital for better life cycle management of valuable assets
- Knowledge of publicly available pre-trained encoders can be utilized to build new models with few images
- Semantic segmentation model accurately segments creep voids in SEM images
- Information about the density and area fraction of creep voids is obtained within a few seconds
- Further work on segmentation of various types of creep voids and generalization of the trained model