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Prediction of Weld Area Based on Image Recognition and Machine Learning

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Abstract

Modern aluminium alloy welding techniques like laser oscillation welding can successfully reduce weld porosity brought on by the physical and chemical characteristics of aluminium alloy. Since it has a significant impact on the mechanical qualities of welded connections, the weld area is frequently used as an evaluation index of geometric attributes to assess the welding quality. In this paper, a method for predicting the weld area for laser oscillation welding of 6061 aluminium alloy is proposed. The cross-sectional area of the weld is computed using image recognition technology from the metallographic micrographs of welding trials, and the inaccuracy of the recognised weld area is less than 8.8%. Additionally, alternative prediction models for the weld area are created by machine learning methods, such as linear regression, under varied process circumstances.

Keywords: Metallographic • Alloy • Laser • Oscillation

Introduction

Manufacturing data has grown at a never-before-seen rate as a result of Industry 4.0 and Internet of Things developments in digitalization. This expands the potential of data-driven techniques for industrial process monitoring, such as machine learning (ML). In this paper, we provide ML pipes for resistance spot welding quality control. Previous methods mainly concentrated on estimating welding quality using information gathered in lab or experimental settings. In contrast to welding being a continuous process with a regular dynamics and production cycles brought on by maintenance, they tended to perceive welding operations as independent events back then. Additionally, model interpretation based on engineering expertise, a significant and typical activity in the manufacturing business has largely gone unnoticed [1].

A digital camera with high resolution is used to take photographs of the shielded metal arc welding (SMAW) process's acceptable beads, partial fusion, and spatter. To extract the geometrical shapes of surface flaws and acceptable beads, image processing techniques such blurring, thresholding, morphological operations, and contouring techniques are applied to the images. On the contour dataset, machine learning models are constructed using the convolutional neural network (CNN) and ResNet50. To create superior weldments, the classifiers in the current study use image processing to determine the surface fault. Similar predictions with accuracies of 98.37% and 98.64% in categorising acceptable beads and surface weld faults are made by CNN and ResNet50 models [2].

Using a high-resolution digital camera, the shielded metal arc welding (SMAW) process produces photos of spatter, imperfect fusion, and acceptable beads. The geometrical shapes of acceptable beads and surface flaws are extracted from the photos using image processing techniques as blurring, thresholding, morphological procedures, and contouring techniques. The contour dataset is used to create machine learning models using the convolutional neural network (CNN) and ResNet50. In the current study, classifiers use image processing to identify the surface flaw in order to create better weldments. In identifying the permissible beads and the surface weld flaws, CNN and ResNet50 models have prediction accuracies of 98.37% and 98.64%, respectively.

These days, manufacturing industries create predictions for the optimization of the mechanical and microstructure properties of manufactured mechanical components using the power of machine learning and data science algorithms. The use of these algorithms lowers the expense of research while also speeding up experimentation. The goal of the current study is to estimate penetration depth utilising Supervised Machine Learning techniques, including Robust Regression, Random Forest, and Support Vector Machines (SVM). Two elements of the AA1230 aluminium alloy were fused together using a Friction Stir Spot Welding (FSSW). Rotational Speed (rpm), Dwelling Time (seconds), and Axial Load (KN) are the three input parameters that make up the dataset, which was used to train and evaluate machine learning models [3].

Bosch RSW technologies generate substantial amounts of heterogeneous data and are fully automated. As a result, in this work, we emphasise data analysis, particularly on machine learning (ML), for quality monitoring. RSW footnote 1. Keep in mind that ML techniques have demonstrated their strong potential for quality monitoring, and as a result, industry attention is growing for them. The ability of machine learning (ML) to anticipate quality by using statistical theory to construct mathematical models is one of the causes. As a result, ML makes it possible for computers to infer information from data without explicit programming. Furthermore, ML techniques are crucial because accurate welding quality assessment can reduce or even eliminate the need for pricy destructive welding quality measuring [4,5].

Literature Review

When recognising picture faults, deep learning algorithms are utilised to find weld image flaws. In this study, a transfer learning approach based on convolutional neural networks is suggested for the problem of deep neural network model recognition on picture data sets for weld fault detection. The pretrained model is used to design interdomain heterogeneous transfer learning, which is then used to transfer the pretrained model from the source data domain to the target data domain based on the differences in content between the source and target data domains. The effectiveness of the transfer learning in identifying weld inspection image defect is then confirmed by fine-tuning the entire network [6].

The advancement of ray detection technology has led to a rise in the use

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of inspection methods using various imaging modalities, including radiographic inspection and ray real-time imaging. Although using film wastes time, pollutes the environment, is inefficient, and has other drawbacks, some domestic heavy equipment manufacturing companies still use radiographic film development technology to detect defects in large wall thickness welded parts. However, using AB-level or B-level blackness of the film can be very sensitive to detect the presence of tiny defects in the weld information, which cannot be replaced by real-time imaging [7].

Discussion

Cloud computing, GPU, computer vision, speech recognition, natural language processing, and human-computer gaming based on deep learning have gained rapid development with the advancement of computer technology and further improvement of performance in all aspects, as well as the emergence of Big Data, opening up new paths for many experts and scholars. The development of deep learning has made it unnecessary for researchers to manually extract features from input photos, and it is now capable of learning and recognising the deep features of input images automatically with good results.

Conclusion

Computers and scanning technologies have advanced and found a wider range of applications with the advancement of modern science and technology. Traditional film is transformed to a digital image via a scanner, and real-time imaging also converts analogue signals to digital signals to enable computerised inspection and evaluation points. Based on this, researchers have divided the manual film evaluation procedure into computer processing steps, such as segmenting weld areas, extracting defect features, classifying and identifying defects, and presenting and preserving the final classification results.

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Conflict of Interest

There are no conflicts of interest by author.

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