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Enabling Sustainable Steel Production with Computer Vision

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Abstract. The steel industry is a significant contributor to global carbon emissions, making the sustainability of it an important area of improvement. Existing decarbonisation solutions such as carbon capture, hydrogen-based steelmaking and electrolysis have been explored but the potential of artificial intelligence, and specifically computer vision, is yet to be realised. Computer vision has shown competence in a range of steelmaking applications but has not been linked to sustainability in the industry. This lack of awareness results in missed opportunities for sustainable development. The introduction of this paper connects computer vision to steelmaking and sustainability, which is followed by a literature review based on existing technologies, and the description of a future vision of steelmaking. The paper will be finalised with conclusions.

Keywords. computer vision, deep learning, steelmaking, manufacturing, sustainability

1. Introduction

The United Nations (UN) defines sustainability as "meeting the needs of the present without compromising the ability of future generations to meet their own needs", which is achievable by addressing the interdependent and mutually beneficial economic, social and environmental pillars of sustainable development on local, national, regional and global levels [1, 2]. The steel industry is a major contributor to global sustainability challenges due to pollution, high energy demand and safety hazards. However, due to its high impact it also possesses the potential to be a major part of the solution [3].

Sustainable steelmaking is a controversial topic due to being a cornerstone of the urbanisation process of developing countries [4]. Furthermore, traditional approaches to sustainability have relied on flawed technologies such as biomass substitution, carbon capture and storage and green and blue hydrogen, which are limited technically and economically [5–8].

Computer vision (CV) is a branch of artificial intelligence (AI): a strong driver of industry 4.0 and the most powerful emerging technology that exists today. Computer vision refers to a range of image and video data processing techniques that can analyse data to describe the world we see around us, or in some cases, the world around us that we are unable to see. Computer vision has already revolutionised the automotive industry with self-driving cars, the agricultural industry with crop surveillance, healthcare with automated medical diagnosis and the manufacturing industry is no exception with automated inspection systems for assembly and surface defects, automated labelled character recognition on parts, industrial robot vision, and more [9–14]. In this paper, a literature review will cover some existing studies in the area, followed by a description of how computer vision in steelmaking could look in the future. Conclusions will then finalise the paper.

2. Literature Review

The aim of this paper is to bring attention to the importance of integrating computer vision technology with steelmaking to mitigate the consequences of inherently unsustainable practices. This literature review will outline existing examples that integrate the two fields.

2.1. Surface Defect Inspection

Surface defect detection consists of two steps: localisation and classification. During localisation the object's location is identified, and during classification the type of object is identified. In the past, steel strip surface defect detection methods were mostly manual which resulted in a high false detection rate [15]. For the most experienced workers the detection rate of defects was around 80%, leaving one in five defects overlooked [15]. Poor quality steel leads to economic and ecological consequences due to wasted resources, as well as social consequences due to the damaged reputation of a company manufacturing poor-quality steel which takes many years to recover from [16].

Table 1 shows a comparison of existing methods of surface defect inspection, where mAP is the mean average precision which normally refers to the average of areas under the precision-recall curves generated for each predicted class during detection or segmentation. Equation 1 and Equation 2 show the precision and recall respectively, where TP is true positives, which is the number of correct predictions. Ground truths refer to the actual number of instances.

Table 1: Comparison of surface defect detection methods based on mean average precision and frames per second

Method	mAP	FPS
DCC-CenterNet	79.41	71.37
MSFT-YOLO	75.70	29.10

$$precision = \frac{TP}{\#predictions} \tag{1}$$

$$recall = \frac{TP}{\#groundtruths} \tag{2}$$

Existing work includes a model called DCC-CenterNet that was comprised of CenterNet, a dilated feature enhancement model (DFEM) and a prediction head which was tested on different defects (crazing, inclusions, patches, pitted surfaces, rolled-in scale and scratches, punching, weld line, crescent gap, water spot, oil spot, silk spot, rolled pit, crease and waist folding) [17]. MSFT-YOLO is another model which integrates YOLOv5, a transformer and a bidirectional feature pyramid network (FPN) and was tested on crazing, inclusion, patches, pitted surfaces, rolled-in scale and scratches [18].

2.2. Microstructural Analysis

Microstructural analysis is also evolving through computer vision. Classification and segmentation are either used individually or together. Segmentation is pixel-level prediction of objects, making it more accurate than detection and more appropriate for tasks involving microstructure due to their detail. Microstructural analysis is crucial for determining the physical and chemical properties of a material and has normally been conducted using human judgment, resulting in uncertainties [19]. Furthermore, traditional methods are time consuming and challenging for workers reducing productivity and reliability of their observations [20].

Studies that involve the use of computer vision for microstructural analysis are compared in Table 2. One achieved microstructural segmentation and subsequent analysis of ultra-high carbon steel using a PixelNet variant, where distinction was made between the proeutectoid cementite network, fields of spheroidite particles, ferritic matrix within the particle-free denuded zone near the network, and Widmanstätten laths [21]. The segmentation provided a basis for describing cementite particle size and denuded zone width distributions [21]. Additionally, a deep convolutional neural network (DCNN) was used to classify eight different types of steel microstructure images obtained from light optical microscopy (LOM) [22].

Table 2: Comparison of microstructural analysis models based on accuracy

Method	Accuracy
PixelNet Variant	86.5%, 92.6%
DCNN	99.8%

2.3. Health & Safety

Safety within steelmaking is a large contributor to the social pillar of sustainability. According to the UK Health and Safety Executive (HSE), 123 workers were killed in work-related accidents in 2021/22 in the UK [23]. The leading sector for this was construction with 30 deaths, followed by manufacturing with 22 deaths [23]. Steel production plays a large part in fatal work-related accidents, especially considering the type of equipment used in steel production such as hot metal ladles, blast furnaces, basic oxygen furnaces, electric arc furnaces, hot and cold rolling mills, coating machines and more.

Existing computer vision approaches to improve steelmaking include one study where Faster RCNN was trained on 4500 images with labelled helmets as part of a safety helmet wearing detection system for steel factories, which achieved an mAP of 71.21 [24]. Another study proposed a crane hook detection system to ensure the hook and ladle trunnion are properly matched when lifting ladles, preventing major accidents [25]. The approach taken was to use Mask R-CNN (a segmentation extension of Faster R-CNN), to segment the crane hook and check if it is matched correctly with a painted trunnion

[25]. Across 100 images, the proposed model achieved a segmentation accuracy of 92% and a safety judgment accuracy of 96% [25].

3. The Future of Steelmaking

Since the dawn of industry 4.0 (considered to be 2011 [26]), factories have become increasingly smart through addition of many sensors to equipment and products, which with digitalisation and ubiquitous computing, has led to a new degree of autonomy [27]. As AI has begun to flourish, this degree of autonomy has burgeoned.

Automatic steel surface defect detection has become a prominent area of CV research and a range of systems have been implemented that largely extend the two studies discussed in the literature review. The accuracy, speed and computational efficiency at which inspection is done is increasing. The continuously improving autonomy and analysis capabilities of these systems will result in less material wastage, less energy wastage and reduced quantities of poor quality steel on the market. Also, process reliability will increase and responsibility on workers will be lightened due to the reduced level of required supervision.

CV-powered microstructural examination provides benefits such as improved quality of observations and analyses, shortened observation times, process reliability and reduced human resource requirements. These all have positive economic impacts, as well as potential social improvements due to the lightening of worker responsibility.

Microstructural analysis technology advancement also promotes capabilities of microstructural tuning for sustainable alloy design [28]. Building recyclability directly into the design of steel requires avoidance of over-designed alloys and utilisation of materials from a limited composition spectrum whilst property tuning through microstructural adjustment [28]. Since computer vision technology has the potential to surpass abilities of existing experts, it could assist in improving the recyclability of future alloys. Additionally, there is the potential to make previously undiscovered microstructural observations since AI has already found undiscovered nanostructures and proteins in other fields of research [29, 30]. New discoveries are encouraging to existing and prospecting researchers, as well as the general public which is socially beneficial.

Safety is a major element of the social pillar of sustainability. The more CV is integrated into steelmaking, the safer it will become even as a by-product due to the remote element. When targeted specifically, it has applications such as ensuring safety equipment is worn at all times and processes are operated correctly by workers to avoid accidents. In future, entire steelworks could be monitored with automatic compliance checks in real-time with alert responses if any safety rules are not adhered to, and early warning systems will alert when processes are deviating from control allowing timely rectification. This would revolutionise safety in steelmaking because it is much harder to make mistakes with hard engineered safety systems in place, as opposed to just following procedure.

All the examples mentioned in this section portray the current progress of integrating CV into steelmaking for sustainable development. The future possibilities are exciting and are likely to lead to fully-automated inspection, process control and transportation of materials. Additionally, there will be invaluable microstructural examination insights and significantly improved site safety.

4. Conclusions

This paper has described recent advances in computer vision and how they will help to improve the sustainability of steelmaking. The main benefits of computer vision in steelmaking include improved safety, improved product quality, improved productivity, reduced waste, reduced stress of workers and increased technological insight. These benefits directly improve the environmental, economic and social sustainability of steelmaking.

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