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Original Research

Automatic intelligent inspection system for crankshaft grade detection based on machine vision and deep learning

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ABSTRACT

The adaption of main bearings with crankshaft grades is an important consideration in bearing installation tasks. If an operator is not careful, it will cause a significant decrease in the quality of the final assembled engine and also cause some defects. Machine vision systems have the potential to implement autonomous error detection that can significantly reduce inspection time and lead to more frequent, precise, and objective inspections. Herein, an inspection system was developed, capable of automatically detecting crankshaft grades from crankshaft images. A specific lighting condition was designed to obtain proper images of the crankshafts. An efficient diagnostic approach based on the semantic segmentation method was presented in this regard. Two different convolutional neural network (CNN) architectures, including MobileNet and VGG19, were trained and evaluated. MobileNet was revealed to be the best compromise between accuracy, with an IoU-Score of 85%, and validation time, with 0.2 ms for discovering the characters engraved on the crankshaft. According to the obtained results, the proposed approach could be used as an efficient, accurate, and fast tool for the automatic detection of crankshaft grades in bearing assembly stations.

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1- Introduction

The engine industry is one of the most active industries in the world, as it is related to various industries such as automobiles, steel, oil, agriculture, etc. Engine, as the heart of all kinds of machines, is made up of different components with specific tasks. The engine performance depends on the design and quality of its components and how they are assembled in production lines. Today, engine factories, in addition to using human resources, have turned to automatic systems for the operation and inspection of assembly processes. These systems lead to an increase in the quality of the assembly process and ultimately increase the quality of the final product. Among the different engine parts, some components are responsible for the main tasks, so the quality of their design, construction, and assembly is more important. The crankshaft and its plain bearings are among these parts. The plain bearing must conform to the irregularities of the journal surface of the crankpin. It should have sufficient wear resistance at the running-in stage, high fatigue strength at high pressure, and adequate seizure resistance at the boundary lubrication regime. This component also has the following tasks; stabilizing the shaft, forming a sufficient hydrodynamic lubricating film for every operational state, absorbing dynamic loadings [1], and protecting of crankshaft journal surface from scratching, wearing, and damaging by absorbing dirt, metal, or other hard particles and resisting corrosion from acid, water and other impurities in the engine oil [2].

After manufacturing crankshafts, due to the size difference in the diameter of crankshaft journals, some characters are engraved on the crankshaft counterweight, called crankshaft grade, which are indicators for choosing the right plain bearings that should be used for it. If the operator does not install the correct plain bearings by the engraved grade, the engine will deviate from the standard designed value and cause some problems such as oil pressure drop, lack of lubrication, increase in engine noise, bearing defects, and other failures. The extraction of the engraved characters by the operator is usually difficult due to the poor contrast with the background [3]. Also, the small size of the characters causes eyestrain and so makes errors. Therefore, it is vital to establish an intelligent system independent of human senses to recognize the characteristics of crankshaft grades in assembly stations to avoid operator errors.

Many researchers have dealt with the field of text and character recognition, for example, Qadri and Asif presented an efficient automatic vehicle number plate identification system by using an optical character recognition technique. The system was capable of identifying vehicles, extracting number plate regions, and then detecting plate characters [4].

Patil and Dhanvijay developed a technique to recognize machine-printed characters by blob detection and image processing methods. They achieved more accuracy for printed character identification and edge detection by blob detection than optical character recognition (OCR) and optical character verification methods (OCV) [5].

In another research, Patil and Dhanvijay used computer vision to identify engraved characters for the determination of engine and chassis numbers. They claimed that the proposed OCR system works efficiently in real-time applications under poor illumination conditions. The system was able to recognize engine and chassis numbers set in any font with almost 99.99% accuracy [6].

Verma et al proposed an automatic container code recognition method using spatial transformer networks and connected component region proposals and achieved an accuracy of about 95% in identifying the complete container code [7].

Wu et al developed a vision-based system based on deep learning for automatic detonator code identification and achieved 99.18% accuracy in end-to-end recognition [8]. Yasak and Kocer presented different models for the classification of industrial circular metal objects and used OCR to character segmentation by deep learning method [9].

Capela et al used a deep learning method to detect labels on car parts. To this end, they prepared a dataset of 321 images under experimental conditions and used Yolov3 for detection, which achieved an Intersection over Union (IoU) (IoU)-Score of 87% [10].

Pandey et al utilized CNNs for text detection, and employed Gabor filters as part of data augmentation to enhance their dataset. They evaluated the method using the IIIT5K dataset and achieved an accuracy of 95.2% [11].

Ren et al discussed systematically a brief history and the state of the art in illumination, image processing, and image analysis in the field of vision-based inspections. They emphasized that superb optical illumination platforms are the prerequisite to obtaining high-quality images [12].

To the best of my knowledge, no research has been reported on the development of an intelligent vision-based inspection system to detect crankshaft grades in real applications. Therefore, considering the necessity of establishing such an inspection system in production lines, this paper presents an efficient, accurate, and fast method to detect the crankshaft grade for an internal combustion (IC) engine in a real factory environment. The contributions of this study can be summarized as follows:

- A new dataset was developed to analyze the effectiveness of the state-of-the-art letter detector in an industrial environment.
- A lighting system was designed to make a constant lighting condition without noise on images.
- An augmentation technique was used to improve the performance of the trained model.
- A precise model was developed to detect crankshaft grade in a real industrial environment.

2- Materials and Methods

2-1- Experimental setup

In this research, the experiments were implemented in a bearing assembly station of a four-cylinder engine production line. In that station, the engine block equipped with the crankshaft is entered by a conveyor. The operator must install the appropriate bearings according to the grades engraved on the crankshaft. After finishing the bearings assembly, the engine block is gone out from the station.

The imaging system used in this research comprised of a camera Tcam 1710K, and the following settings were used to take the images: manual focus; flash - no; compression – JPEG; resolution – 0.512 MPixels (480×480px).

To record images, the camera was connected to a computer with a USB port. Pycharm software was used to communicate between the imaging equipment and the computer and to store and then analyze the images.

The scenario of image capture was such that when the engine block enters the bearing station, a control signal is received from the production line automation using an Arduino board connected to the computer. Then, the camera takes an image from the crankshaft and transfers it to the computer for processing and subsequent analysis steps.

The performance of the machine vision system is highly dependent on lighting conditions. Since there is a need to keep inspection system performance fixed during all operating times including day and night, it is important to design and establish a lighting system to provide a constant light condition for the object and help to create the same images in terms of optical specifications like brightness and contrast. Due to this importance, many researches and various solutions have been presented for light control and the manner of designing a successful lighting system [13].

Lighting for shiny objects is challenging because a little direct beam on them will greatly be reflected to the camera and create very bright and white regions, namely light glare, in the photo. These areas cause a part of the object’s image to be lost and the detection process to fail. The crankshaft is taken into account as a shiny object, and improper lighting makes the crankshaft grades not readable. Therefore, designing the right lighting condition for this component was one of the main challenges of this research. The lighting system designed in this work included: 1) a tunnel with a dimension of

124×135×112 mm to isolate the crankshaft from ambient lights, and 2) a 0.5 m LED strip as a light source to create a constant optical condition. To prevent the creation of light glare on the crankshaft piece, the light source was placed parallel to the crankshaft at a distance of 35 cm). With the designed lighting system, there was no reflection on the images taken of the crankshaft in the region of the grades engraved, and all of them were visible as much as possible. Figure 1 shows an example of the crankshaft image captured. As can be seen from this figure, the light without any glare has completely uniformly been emitted to the crankshaft causing the grades engraved on the counterweight to be read well.

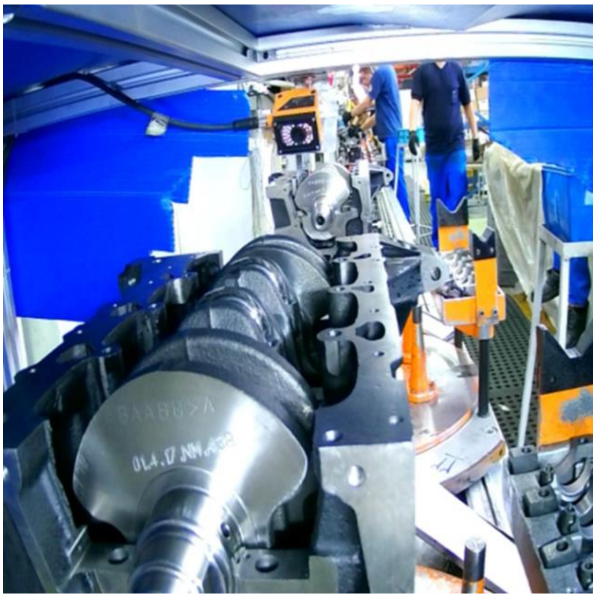

Figure 1 The image was taken from a sample crankshaft using the designed lighting system

2-2- Dataset construction

The crankshaft grade in the four-cylinder engine under study had three cases of A, B, and C which were equal to the main bearing outer diameter of about 1.848, 1.854, and 1.860 mm, respectively. To establish an image database, the picture of crankshafts with different combinations of these three letters was captured. In total, 323 images of different crankshaft grades including repetition were collected in the bearing assembly line.

Due to the usual difficulties in imaging tests and needing human resources to annotate the images, collecting a large number of images for training models is often a challenge. One of the well-known tools to enlarge the working dataset is the data augmentation (DA) technique [14]. Synthetic examples from a set of original images could be generated using DA. For this work, various transformations with random values are applied to original images, and new ones are generated. Changes in smoothness, sharpness, contrast, brightness, rotations, translation, zoom, and random cropping are some instances of transformations [15].

This paper utilized DA to enrich the database. To this end, two different examples were generated from each of the crankshaft images by grayscaling and filtering (Figure 2). The filtering task was done using the Sobel operator. Accordingly, the number of images in the database increased to 969. In the next step, all datasets were split into two groups: training (~75%) and validation (~25%). Table 1 shows briefly the division of the database.

Table 1 Database division used in this research

Dataset	Description	Training	Validation
A	Original images	243	80
B	Original+augmented images	729	240

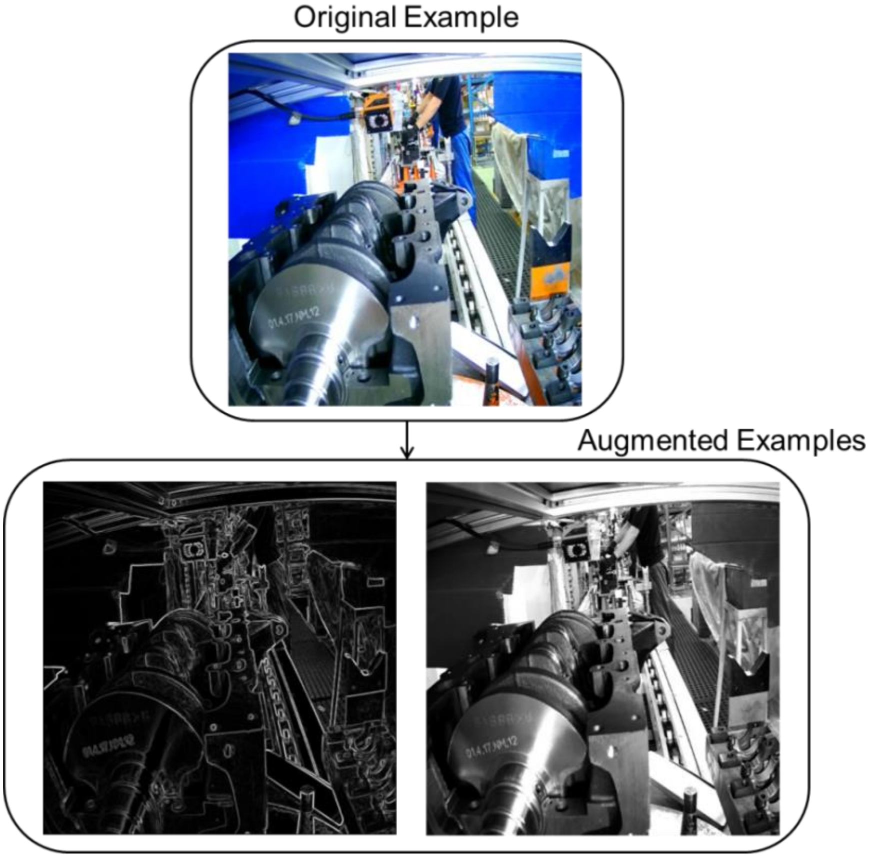

Figure 2 Augmented examples generated from an original image of crankshaft grade

After splitting the dataset, the annotations were made by an expert, assuring the high quality needed for developing the models. Annotations were created using the PixelAnnotationTool_x64_v1.3.2. To define the classes, A was painted red with the letter A, yellow with the letter B, and blue with the letter C. Figure 3 illustrates annotations made on two specimens of the crankshaft image.

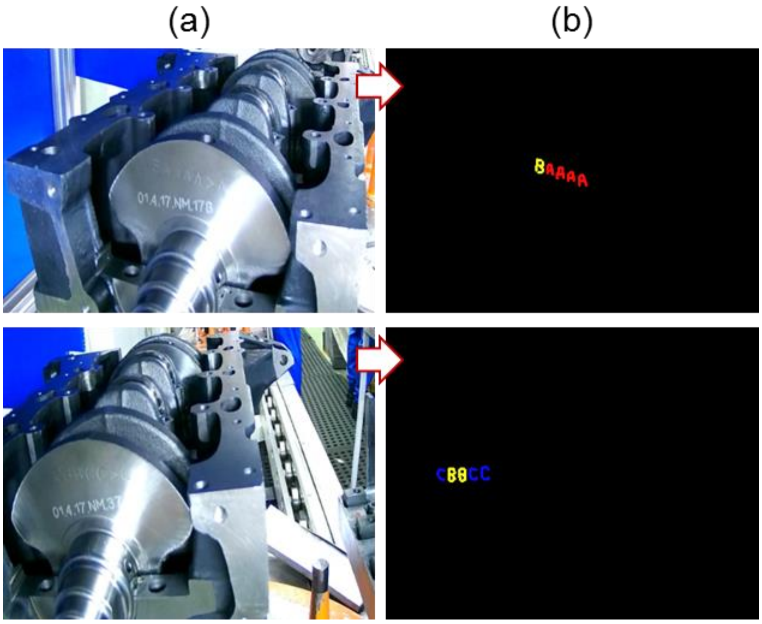

Figure 3 Examples from the dataset created for detection: (a) images; (b) labels

2-3- Methodology

As mentioned before, the crankshafts under study had five main bearings. Considering that in the crankshaft, for each main bearing, one grade is inserted among three cases of A, B, and C, there will be 3^5 different cases for crankshaft grade. Because it is practically impossible to perform imaging tests for such a large number of different cases, therefore, the classification approach could not be implemented as a solution. Hence, a way has to be found to be able to recognize the grades correctly, without the need to take pictures of 3^5 various cases. In this research, a pixel-wise segmentation method is chosen to overcome this challenge.

One of the hypotheses in this regard is that if the artificial intelligence model could learn and recognize the crankshaft grade characters, their position would no longer be important because when the grades are identified, their position will be automatically determined. For this work, CNN-based image analysis is recommended in this research. CNN is a type of neural network providing a deep learning model. It includes three various layers namely, pooling, convolutional, and fully connected layers each one playing a specific role. Using CNN, it is possible to explicitly extract information from visual data [16]. Every CNN layer transforms the input volume to an output volume of neuron activation, eventually leading to the final fully connected layers, resulting in a mapping of the input data to a 1D feature vector. CNN has extremely been successful in computer vision applications. Deep neural networks are also very effective in semantic segmentation, which is labeling each region or pixel with a class of objects/non-objects. In image analysis, semantic segmentation is the task of clustering portions of an image together that belong to a similar object class [17]. It locates the exact pixels of each object instead of only the bounding boxes [18].

In this research, a semantic segmentation technique was employed for identifying grades engraved in crankshafts. As far as is known, a method similar to the successful automatic inspection system of character detection on engine metal parts which was developed in this study with a deep learning method has not been reported in the literature. To this end, U-Net architecture with VGG19 [19] and MobileNet [20] backbones were used and compared. They utilize a pre-trained model on the ImageNet dataset [21] for feature extraction layers. The architectures were constructed by the framework Keras 2.9.0 with TensorFlow 2.9.1 as the backend. Figure 4 shows the flowchart of the proposed procedure. The configurations of the computer used for training and testing were GPU: NVIDIA GeForce RTX 3060 8 GB; RAM: 32 GB; CPU: Intel® Core™ i5-7700 K CPU @ 4.20 GHz × 8; operating system: Microsoft Windows 10.

3- Results and Discussion

To fine-tune CNN models, Stochastic Gradient Descent (SGD) with momentum 0.9 and Root Mean Square propagation (RMSProp) were employed, respectively. The models were compiled using the Categorical Focal Loss function. The Adam with default parameters $\beta1=0.9$ and $\beta2= 0.999$ was chosen as the optimizer. For training the detection models, the input size, batch size, and initial learning rate (LR) were set to 480×480px, 1, and 10^{-4}, respectively.

Since, in this work, the achievement of an efficient detector and accuracy/speed trade-off evaluation were targeted, as mentioned before, it considered two different training scenarios: 1) training with only original images, which means dataset A in Table 1, 2) training with original+augmented images, means dataset B in Table 1.

To evaluate the finetuned models, IoU-Score and validation time metrics were obtained for both training scenarios. The computational performance metrics of the CNN models are given in Table 2. The two models provided the same result regarding the number of epochs needed for reaching convergence. But MobileNet weights number was significantly lower.

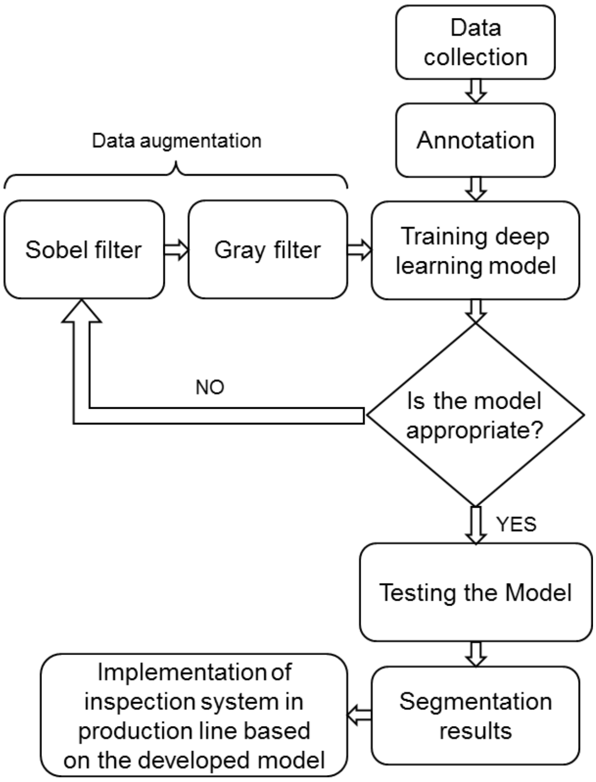

Figure 4 Flowchart of the current research

Table 2 Comparison of the models regarding epoch and weight number

Model	Weights number	Epoch
VGG16	138.4×10^6	100
MobileNet	4.3×10^6	100

Table 3 compares the functional quality of the segmentations in the form of IoU-Score and the validation time of each model in their best epochs. For dataset A, the model MobileNet with 82.1% IoU-Score showed the best performance. For dataset B, although the results were almost close, MobileNet again was the best with 85% IoU-Score.

To demonstrate the effectiveness of the models for real-time applications, the time consumed to segment the validation images was compared (Table 3). This further analysis was needed to determine how the models behave, regarding time-efficiency performance, when utilized after training. The MobileNet with a validation time of 0.2 ms was faster than VGG16 for the two datasets. Consequently, the comparative analysis showed that the model MobileNet had the highest capability to segment the crankshaft images and disclose the engraved grades, due to its best accuracy and lowest validation time.

Table 3 Comparison of performance metrics between the models

Dataset	Model	IoU-Score (%)	Validation time (s)
A	VGG16	76.9%	0.84
	MobileNet	82.1%	0.2
B	VGG16	81.4%	0.84
	MobileNet	85%	0.2

The CNN training with MobileNet architecture for segmentation was implemented with 100 epochs in 49.8 min. Figures 5 and 6 illustrate the evolution of IoU-Score and loss metrics in the training and validation sets along the epochs for datasets A and B, respectively. According to Figure 5, for dataset A the model validation loss improved with an almost constant changing slope up to the last epoch. The model indicated the highest validation IoU-Score with a value of 82.1% in the 81st epoch.

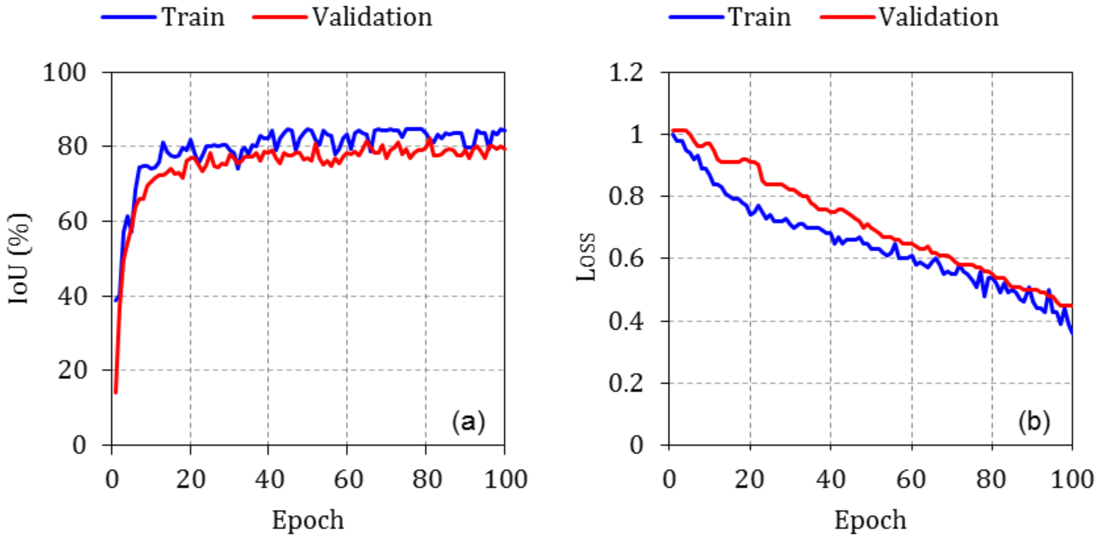

Figure 5 Evolution of (a) IoU score and (b) loss during training and validation of the crankshaft grade semantic segmentation model with original data

Referring to Figure 6, for dataset B the model validation loss decreased linearly until the 42th epoch; afterward, it stayed almost constant until the last epoch, except for a jump in the 86th epoch. Training the network in this stage provided roughly a 3% increase in the validation IoU-Score compared to when no augmentation technique was used in the dataset so an 85% validation IoU-Score was achieved in the 75th epoch.

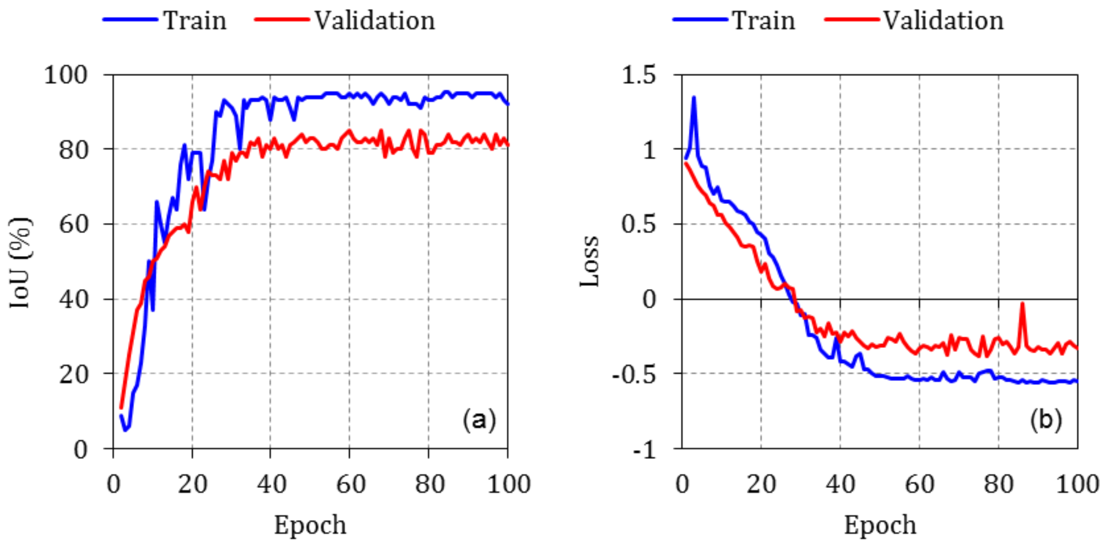

Figure 6 Evolution of (a) IoU score and (b) loss during training and validation of the crankshaft grade semantic segmentation model with original and augmented data

An example of segmentation performed by the MobileNet on a test image is shown in Figure 7. As can be seen, all grades engraved in the crankshaft were identified well in terms of character, number, and location.

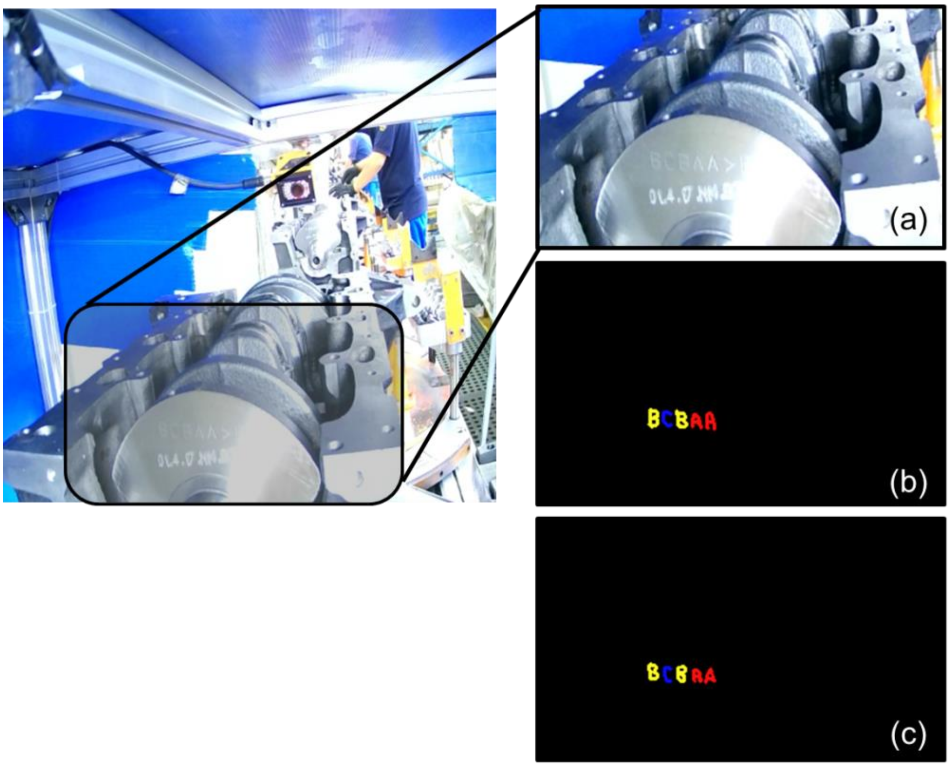

Figure 7 A cropped view of (a) the original image (b) the segmentation mask applied to the original image (c) segmentation provided by the CNN with MobileNet architecture

4- Conclusion

To automatically control the production processes, this paper presents a vision-based intelligent system for accurate and fast identification of crankshaft grades in bearing assembly stations. The system's output can help with the correct fitting of the bearings in the relevant assembly station and prevent human errors in this regard. To this end, the imaging tests were first performed using the designed lighting system. Then, to avoid overfitting the deep learning models, the dataset was enlarged with a data augmentation technique. The results showed that at least a 3% improvement was achieved in the performance of the deep learning models by data augmentation. It was demonstrated also that by applying the semantic segmentation method it is possible to identify successfully crankshaft grades. After training and evaluating two different CNN models, MobileNet is recommended according to IoU-Score and validation time metrics. The performance of VGG19 was significantly less than MobileNet. A high level of 85% correctness with the metric IoU-Score and the validation time of 0.2 ms were achieved based on MobileNet. It is believed that the proposed inspection system could effectively be used in the engine production lines for crankshaft-grade detection in real applications. Future works will focus on other analysis methods with the purpose of the accuracy rise.

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مقاله پژوهشی

سامانهٔ هوشمند بازرسی خودکار برای تشخیص رتبه‌بندی میل‌لنگ مبتنی بر بینایی ماشین و یادگیری عمیق

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اطلاعات مقاله

کلیدواژه‌ها:
بینایی ماشین
یادگیری عمیق
خط تولید موتور
رتبه‌بندی میل‌لنگ
بازرسی خودکار

چکیده

انطباق یاتاقان‌های اصلی با رتبه میل‌لنگ، یک ملاحظهٔ مهم در عملیات نصب یاتاقان است. اگر کاربر خط تولید دقت نکند، باعث کاهش قابل توجه کیفیت موتور نهایی همبندی شده می‌شود و همچنین یکسری ایرادها در آن ایجاد می‌شود. سامانه‌های بینایی ماشین ظرفیت اجرای تشخیص خطای خودران را دارند که می‌توانند زمان بازرسی را به مقدار قابل توجهی کاهش دهند و منجر به بازرسی‌های چندباره، دقیق‌تر و عینی‌تر شوند. در اینجا، سامانه‌ای برای بازرسی توسعه داده شد که قادر به تشخیص خودکار رتبه‌بندی‌های میل‌لنگ از تصاویر میل‌لنگ است. شرایط نوری خاصی برای به دست آوردن تصاویر مناسب از میل‌لنگ‌ها طراحی شد. در این راستا، یک رویکرد تشخیصی کارآمد بر اساس روش بخش‌بندی معنایی ارائه شد. دو معماری مختلف شبکه عصبی پیچشی شامل MobileNet و VGG19 آموزش و ارزیابی شدند. MobileNet نشان داد که بهترین سازش بین دقت، با امتیاز IoU ۸۵ درصد و زمان اعتبارسنجی، با ۰٫۲ میلی ثانیه برای آشکارکردن حروف حک شده روی میل‌لنگ است. با توجه به نتایج به‌دست‌آمده، رویکرد پیشنهادی می‌تواند به عنوان ابزاری کارآمد، دقیق و سریع برای تشخیص خودکار رتبه‌بندی‌های میل‌لنگ در ایستگاه همبندی یاتاقان استفاده شود.

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