Bias from the Wild Industry 4.0: Are We Really Classifying the Quality or Shotgun Series?

Riccardo Rosati[1(✉)], Luca Romeo[1], Gianalberto Cecchini[2], Flavio Tonetto[2], Luca Perugini[3], Luca Ruggeri[3], Paolo Viti[3], and Emanuele Frontoni[1]

[1] Department of Information Engineering, Marche Polytechnic University, Via Brecce Bianche 12, 60131 Ancona, Italy
r.rosati@pm.univpm.it

[2] Sinergia Srl, Viale Goffredo Mameli 44, 61121 Pesaro (PU), Italy

[3] Benelli Armi Spa, Via della Stazione 50, 61029 Urbino (PU), Italy

Abstract. The traditional data quality control (QC) process was usually limited by the high time consuming and high resources demand, in addition to a limit in performance mainly due to the high intrinsic variability across different annotators. The application of Deep Learning (DL) strategies for solving the QC task open the realm of possibilities in order to overcome these challenges. However, not everything would be a bed of roses: the inability to detect bias from the collected data and the risk to reproduce bias in the outcome of DL model pose a remarkable and unresolved point in the Industrial 4.0 scenario. In this work, we propose a Deep Learning approach, specifically tailored for providing the aesthetic quality classification of shotguns based on the analysis of wood grains without running into an unwanted bias. The task as well as the collected dataset are the result of a collaboration with an industrial company. Although the proposed DL model based on VGG-16 and ordinal categorical cross-entropy loss has been proven to be reliable in solving the QC task, it is not immune to those who may be unwanted bias such as the typical characteristics of each shotgun series. This may lead to an overestimation of the DL performance, thus reflecting a more focus on the geometry than an evaluation of the wood grain. The proposed two-stage solution named Hierarchical Unbiased VGG-16 (HUVGG-16) is able to separate the shotgun series prediction (shotgun series task) from the quality class prediction (quality task). The higher performance (up to 0.95 of F1 score) by the proposed HUVGG-16 suggests how the proposed approach represents a solution for automatizing the overall QC procedure in a challenging industrial case scenario. Moreover, the saliency map results confirm how the proposed solution represents a proof of concept for detecting and mitigated unwanted bias by constraining the network to learn the characteristics that properly describe the quality of shotgun, rather than other confound characteristics (e.g. geometry).

Keywords: Quality control · Bias · Deep learning

A. Del Bimbo et al. (Eds.): ICPR 2020 Workshops, LNCS 12664, pp. 637–649, 2021.
https://doi.org/10.1007/978-3-030-68799-1_46

1 Introduction

Nowadays, most of the vision instruments for the automation of quality control procedure available on the market focus on quantitative and deterministic analyses (e.g. dimensional control, an inspection of the roughness of materials, etc.), but there is no software instrument that allows the modeling and generalization of all those qualitative analyses that are still executed by highly specialized technicians. Thus, the traditional data quality control process was usually limited by the high time consuming and high resources demand, in addition to a limit in performance mainly due to the high intrinsic variability across different annotators [6]. It is therefore not surprising that the quality control task has quickly established itself as an industrial 4.0 use case. Implementing industrial IoT and vision systems to monitor the health and quality of the instrumentation/products/materials enables manufacturers to support the technicians during the process while reducing resource costs, intrinsic variability and improving productivity.

The application of Deep Learning (DL) strategies for solving the quality control task open the realm of possibilities in order to overcome these challenges. However, not everything would be a bed of roses. Although the potential of DL to learn the discriminatory patterns is very relevant and the range of applications is almost limitless, the inability to detect bias from the collected data and the risk to reproduce bias in the outcome of the DL model pose a remarkable and unresolved point in the Industrial 4.0 scenario. Accordingly, the holy grail of DL is to learn from examples and generalize to situations never seen before. These examples are usually provided by humans and humans are biased by our nature. Examples of bias situations in the application of predictive models could range from sentiment analysis, image classification, job recruiting, adaptive chatbot, recidivism assessment, gender classification and language translation [1]. Research direction aims to detect, rate and mitigate bias of the learning process. However, in the DL scenario, the inability to detect bias situations is mainly due to the lack of understanding of the reason for the algorithm outcome. In fact, usually, DL algorithms are conceived as black-box models, which not always lead to interpret and understand how the algorithm provides the decision rule.

Starting from the lesson we have learned by designing and developing a DL methodology, specifically tailored for providing the aesthetic quality classification of shotguns based on the analysis of wood grains, the aim of the paper is to propose a best practice and a proof of concept for detecting and mitigating unwanted bias in the collected data and in the outcome of DL model, in the Industry 4.0 scenario.

Thus the main contributions of the work in the computer vision and pattern recognition field are summarised below:

- the collection of annotated real dataset composed of 1902 images specifically tailored to solve the aesthetic quality classification of shotguns based on the

analysis of wood grains. Each image, displaying a different view of the shotgun is properly annotated by a high specialized technician;
- the proposing of DL approach based on VGG-16 and ordinal categorical cross-entropy loss in a novel and challenging Industry 4.0 application, i.e. the quality control classification task;
- an in-depth analysis of the DL model to show the risk to reproduce the presence of possible bias in the collected data;
- the proposing of two-stage solution named Hierarchical Unbiased VGG-16 (HUVGG-16) for mitigating the detected bias.

2 Related Work

The Industry 4.0 revolution was triggered by the increasing availability of data, high-computing power and large storage capacity. These conditions have led the ML and DL appealing solutions in different industrial areas such as predictive maintenance [5,14], decision support system [13] and quality control [4,7,19]. Quality-control is a growing area in Industry 4.0 and an important step in every production system. Recently, the increasing amount of data in this scenario lied the foundation for combining DL and machine vision for performing texture classification thus helping to detect production issues and classify the quality of the product [3,16].

Standard DL approaches were employed in [11] to replace costly quality control procedures based on visual inspection during the welds mass production scenario with the aim to improve the defect detection accuracy. They mainly focused on the collection of balanced database and image pre-processing. Deep Neural Network (DNN), Deep Belief Network (DBN) and restricted Boltzmann machine are standard DL architectures that were applied in [18] to perform a visual inspection process in the printing industry 4.0 by using as input a high-resolution optical quality control camera. Similarly, in [12] a standard deep learning strategy fed by images acquired by a camera placed over the assembly line was implemented to predict the quality-control in a smart factor prototype. Differently, the authors in [2] employed as predictors one key-quality index and different process parameters monitored by the control instruments. They applied a DNN consisting of a DBN in the bottom and a regression layer on the top to predict the quality prediction of a complex manufacturing process.

Recently, a DL strategy was adopted for detecting geometric inaccuracy of the laser-based additive manufacturing process [8]. They combined the output of a Convolutional Neural Network (CNN) and the output of an Artificial Neural Network for analyzing the thermal images and include relevant process/design parameters respectively. The overall network was trained to predict the final pointwise distortion prediction. Also in [19] the authors proposed a CNN solution to automatically extract discriminative features of the images for defect detection and at the same time by ensuring a high processing speed which guarantees real-time detection.

The main differences with our work lie in the (i) different application of DL methodology we propose in unexplored and challenging quality-control application (i.e. we are interested to classify the aesthetic quality classification of shotguns based on the analysis of wood grains) and the (ii) different goal we aim to solve (i.e. the detection and mitigation of any unwanted bias in this scenario). The proposed solution to this task and challenges provides the main contribution of the presented paper.

3 Dataset

The commercial classification of wooden stocks is defined in categories ranging from grade 1, which indicates almost veinless wood, up to grade 5 with a very twisted and variegated grain pattern. Each different type of shotgun series manufactured by the company is equipped with a stock belonging to a specific grade class. Today the QC is mainly based on the evaluation of the human eye. The dataset refers to a real industrial case study of Benelli Armi Spa. The detention and conservation are regulated by an agreement between Benelli Armi Spa and Università Politecnica delle Marche.

Table 1. The aesthetic quality level of the collected dataset. All the grades are reported in ascending order together with the relative number of stocks.

Label	# Stocks
1	165
2^-	148
2	212
2^+	177
3^-	168
3	250
3^+	198
4^-	208
4	270
4^+	106

The collected dataset is composed of both left and right side images belonging to 951 different shotguns, for a total of 1902 images with a size of 1000×500 pixels. The stocks have been classified into 4 main grades (1, 2, 3, 4) and their relative minor grades ($2^-, 2^+, 3^-, 3^+, 4^-, 4^+$), resulting into 10 different classes as reported in Table 1. Figure 1 shows an example of stock for each of the 10 classes. The images were acquired with a high-definition RGB camera placed in the top-view configuration. During the annotation procedure, a highly specialized technician accurately inspects the item and assigns the labels of the stock using a custom data annotation platform (see Fig. 2).

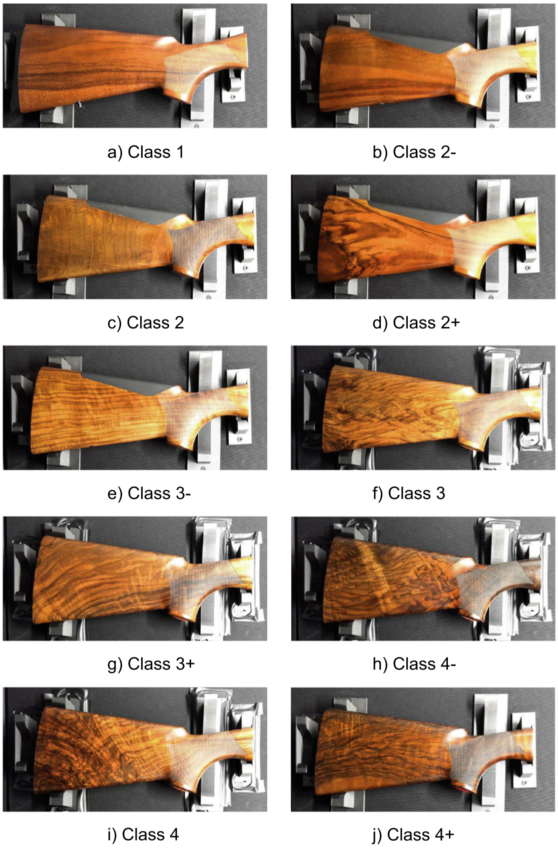

Fig. 1. Example of different stock for each of the 10 classes.

Fig. 2. Custom data annotation platform. The stock is placed in the box where the RGB camera and an industrial lamp are mounted. The annotation software allows the operator to capture the image and to record the grade.

4 Task Definition

The task that we aim to solve is the prediction of the aesthetic quality of shotguns based on the analysis of wood grains. Thus, our inputs are represented by the collected images, while outputs are the 10 different quality classes. Following companies' demands, we divided the problem into different QC tasks sorted according to the level of difficulty established by the company itself:

(a) pediction of middle quality classes: $Y = \{1, 2, 3, 4\}$;
(b) prediction of meta quality classes: $Y = \{1^*, 2^*, 3^*, 4^*\}$,
where $1^* = \{1\}, 2^* = \{2^-, 2, 2^+\}, 3^* = \{3^-, 3, 3^+\}, 4^* = \{4^-, 4, 4^+\}$;
(c) pediction of all quality classes:
$Y = \{1, 2^-, 2, 2^+, 3^-, 3, 3^+, 4^-, 4, 4^+\}$;

where X and Y are respectively the input and the output space. We are interested to learn an agnostic model that classifies the quality classes without being given information about the specific shotgun series. This is because, in the real-industrial case situation, the technician is engaged in the QC procedure within the information of the series of the shotgun is not known a priori.

5 Classification Model

5.1 CNN Architectures

The proposed classification tasks are based on the fine-tuning strategy of state-of-the-art CNNs for image classification, i.e. AlexNet [10], VGG16 [17] and ResNet50 [9]. A transfer learning approach was used to fine-tune the networks on ImageNet pre-trained weights. These architectures are chosen for two main reasons: i) they achieved competitive performances on ImageNet challenge, ii) they are relatively simple (i.e. not too deep), allowing to obtain low-level features for fine-tuning. For all the networks, the last fully-connected layer was modified from 1000 to K neurons, where K is the dimension of output space for each task as defined in Sect. 4.

5.2 Loss Functions

We solved each multi-class classification task a), b) and c) independently by considering respectively i) a standard Categorical Cross-Entropy (CCE) ii) a standard Categorical Cross-Entropy with a target vector which encourages an Ordinal Structure (CCE-OS) and iii) an ordinal categorical cross-entropy (OCCE).

6 Experimental Procedure

6.1 Training Settings

All the networks considered were fed with stock images resized to 224×224 pixels in order to match the ImageNet input dimension. The mean value was removed from each image. We adopted a mini-batch stochastic gradient descend (SGD) optimizer. We have explored the best batch size, the initial learning rate and the momentum in the range {32, 64, 128}, $\{1 \cdot 10^{-4}, 1 \cdot 10^{-3}, 1 \cdot 10^{-2}\}$, {0.8, 0.9} respectively. For each task, we validated these hyperparameters in a separate validation set using a grid-search approach. The number of epochs was set to 30. The best-selected hyperparameters for the quality task are respectively 64, $1 \cdot 10^{-3}$ and 0.8 for batch size, initial learning rate and momentum. The dataset was split by a startified hold-out procedure, i.e. using 60% of images as training, 20% as validation and 20% as test. Images belonging to the same shotgun ID were maintained in the same set. This checking was performed to ensure that the algorithm may be able to generalize across different unseen shotgun stocks. Due to the small dimension of the dataset, data augmentation was performed on-the-fly on the training set, applying horizontal flip, rotation and zoom to original images. To cope with the slight unbalance of the dataset, class weights were computed for weighting the loss function. All the experiments were performed using TensorFlow 2.0 and Keras 2.3.1 frameworks on Intel Core i7-4790 CPU 3.60 GHz with 16 GB of RAM and NVIDIA GeForce GTX 970.

7 Results

In Sect. 7.1, we reported the results for solving the task a) b) and c). Taking into account that the experimental results demonstrated the higher effectiveness of OCCE with respect to CCE-OS, we decided to report the classification performance related to standard CCE and OCCE. Afterward, we described how we have detected unwanted bias for solving this task in Sect. 7.2. Finally, we propose our strategy and related results to mitigate the detected bias in Sect. 7.3.

7.1 Classification Performance

Table 2 shows the classification performance of VGG-16, ResNet50 and AlexNet for solving task a), b) and c) using the standard CCE loss on the test set.

For each task, the VGG-16 overcomes the ResNet50 and AlexNet in terms of Accuracy, Recall, Precision and F1. Hence, we show in Table 3 the performance of VGG-16 using the CCE and O-CCE as loss functions for solving tasks a), b) and c).

The O-CCE loss is more reliable for solving all tasks. The performance of the model decreases according to an increase in the difficulty of the task. Figure 3 shows the confusion matrices of the best performing model (VGG-16 Ω-CCE) for solving task a), task b) and c).

7.2 Bias Detection

Starting from the classification performance extracted in Sect. 7.1, we go further by analyzing any possible unwanted bias that may influence the classification performance. In particular, the bias may be unknown and embedded in

Table 2. Classification performance of VGG-16, ResNet50 and AlexNet for solving task a), b) and c) using the standard CCE loss on the test set. The best performing model in terms of F1 is reported in bold for each task.

Model	Accuracy	Precision	Recall	F1
Task a				
VGG16	**0.96**	**0.95**	**0.96**	**0.95**
ResNet50	0.92	0.92	0.93	0.92
AlexNet	0.95	0.94	0.95	0.94
Task b				
VGG16	**0.91**	**0.87**	**0.90**	**0.88**
ResNet50	0.88	0.82	0.87	0.84
AlexNet	0.89	0.84	0.87	0.85
Task c				
VGG16	**0.63**	**0.61**	**0.62**	**0.60**
ResNet50	0.58	0.56	0.58	0.55
AlexNet	0.60	0.58	0.58	0.56

Table 3. Classification performance of VGG-16 for solving task a), b) and c) using the CCE and O-CCE loss on the test set. The best performing model in terms of F1 is reported in bold for each task.

Loss	Accuracy	Precision	Recall	F1
Task a				
CCE	0.96	0.95	0.96	0.95
O-CCE	**0.96**	**0.96**	**0.96**	**0.96**
Task b				
CCE	0.91	0.87	0.90	0.88
O-CCE	**0.92**	**0.88**	**0.92**	**0.90**
Task c				
CCE	0.63	0.61	0.62	0.60
O-CCE	**0.65**	**0.64**	**0.65**	**0.63**

the dataset/images. In this scenario, following the company's suggestion, we have pointed out different possible bias factors: shotgun series, the instant of time (hour of the day) where the QC is carried out, stock sale id, production time (minutes). Considering the Cramer's correlation we have analyzed how these possible bias factors are correlated with respect to the quality classes $Y = \{1, 2^-, 2, 2^+, 3^-, 3, 3^+, 4^-, 4, 4^+\}$. Table 4 shows that the specific shotgun series is bounded to a specific quality class. Different shotgun series have different exclusive characteristics, i.e. size, shape, color, polishing, plastic insert and other specific treatments. The Cramer's analysis found that the shotgun series is

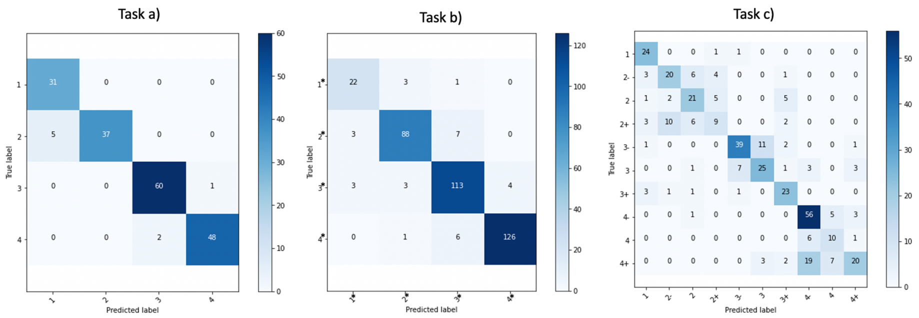

Fig. 3. Confusion matrices of the best performing VGG-16 models with O-CCE loss for solving task a), b), c) respectively.

significantly correlated (0.67, $p < .05$) with respect to the ground-truth quality classes Y. As a consequence, the shotgun series represents a bias in the VGG-16 model.

Table 4. QC classes for each shotgun series

Shotgun series	Code	1	2-	2	2+	3-	3	3+	4-	4	4+
ACCADEMIA GR3+	2	0	0	0	0	0	24	85	9	2	0
RAFFAELLO 2013 GR3	3	0	0	0	11	130	9	0	0	0	0
RAFFAELLO 2013 GR2	4	0	32	149	26	14	3	0	0	0	0
ANNIVERSARY 50° GR4	6	0	0	0	0	0	1	19	101	252	61
828 NIKEL GR3+	8	1	0	0	0	11	176	14	0	0	0
828 CAL20 GR3+	9	0	0	1	0	2	35	70	12	2	0
MONTFELTRO EUROPE GR1	10	151	19	18	4	7	1	0	0	0	0
MONTEFELTRO CLARO GR2	11	3	79	27	105	4	0	0	0	0	0
ARGO E GR4	12	0	0	0	0	0	0	0	8	2	18
FRANCHI EUROPE GR2	13	10	18	17	31	0	0	0	0	0	0
ANNIVERSARY 50° CAL.20 GR4	14	0	0	0	0	0	1	3	35	1	14
RAFFAELLO LIMITED EDITION CAL.12 GR4	15	0	0	0	0	0	0	7	43	11	13

The detected bias is also demonstrated by the high significant Cramer's correlation (0.70, $p < .05$) found between the VGG-16 prediction of task c) and the shotgun series. This fact is also confirmed by exploring the saliency map of the VGG-16 (see Fig. 4, left side) according to the approach proposed by [15]. The most discriminative pattern of the network is placed on the shotgun edge, thus reflecting a more focus on the geometry than an evaluation of the wood grain.

7.3 Bias Mitigation

Our objective is to classify the quality classes without being given information about the specific shotgun series. Thus, the model should be able to classify the quality levels independently from the geometry and the shotgun series.

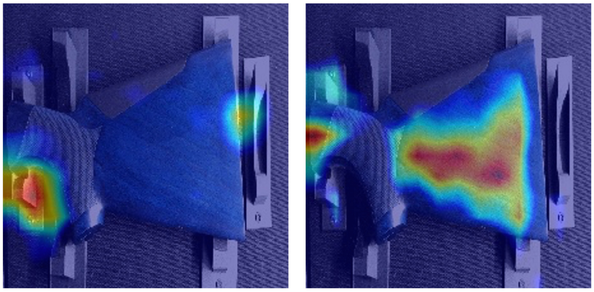

Fig. 4. Saliency maps of a grade 2 stocks belonging to Raffaello series. Left: VGG-16 model trained for task c); right: VGG-16 sub-network trained for solving the quality task on "Raffaello" series.

To achieve this objective we propose a hierarchical network approach, named HUVGG-16 in order to mitigate the bias due to shotgun series. It is designed to learn separately two-stage hierarchical networks that are able to predict respectively the shotgun series (shotgun series task) and the quality classes (quality task). The single network of the first stage predicts all the shotgun series. Based on the shotgun series predicted, we assign a specific second stage sub-network for classifying the quality classes. Each sub-network is conceived to predict only the quality classes associated with respect to the shotgun macro-series. Each macro-series is defined according to the company's knowledge by aggregating shotgun series which have the same geometrical characteristic. Figure 5 shows in detail the workflow of the proposed approach.

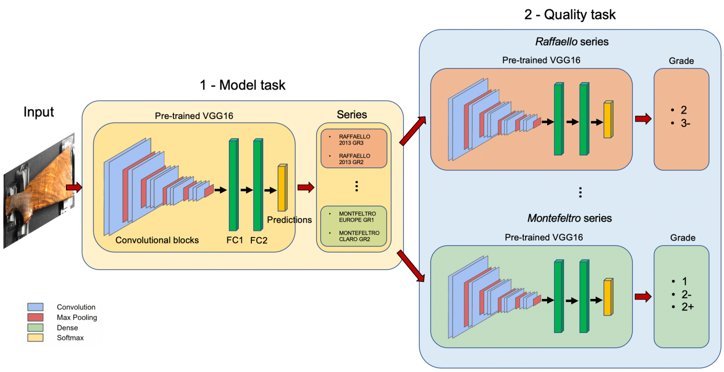

Fig. 5. Workflow of the proposed bias mitigation approach HUVGG-16. The first VGG-16 is conceived to learn the shotgun series (model task) while each sub-networks is specialized to classify the quality classes (quality task) for each shotgun macro-series. Each macro-series is defined according to the company's knowledge by aggregating shotgun series which have the same geometrical characteristic.

The HUVGG-16 approach is shown in Fig. 5. The first VGG-16 is conceived to learn the shotgun series (model task) while each sub-network is specialized to classify the quality classes (quality task) for each shotgun series. For solving the both tasks we employed the O-CCE loss.

The Accuracy, Precision, Recall and F1 of HUVGG-16 for solving the model task are respectively: 0.97, 0.98, 0.97, 0.97.

Figure 6 shows the confusion matrix of HUVGG-16 for solving the quality task on Raffaello and Montefeltro series. In particular, we focus only on the most numerous quality classes (i.e., 2 and 3- for Raffaello series and 1, 2+ and 2- for Montefeltro series). For Raffaello series the Accuracy, Recall, Precision and F1 are respectively: 0.95, 0.94, 0.96, 0.95; for Montefeltro series the Accuracy, Precision, Recall and F1 are respectively: 0.83, 0.85, 0.84, 0.80. Accordingly, the extracted saliency maps are constrained to focus on wood grains rather than the geometrical edges (see Fig. 4 right side). Thus, this strategy allows to alleviate the bias by separating the two task and providing the prediction of quality classes for each shotgun macro-series model.

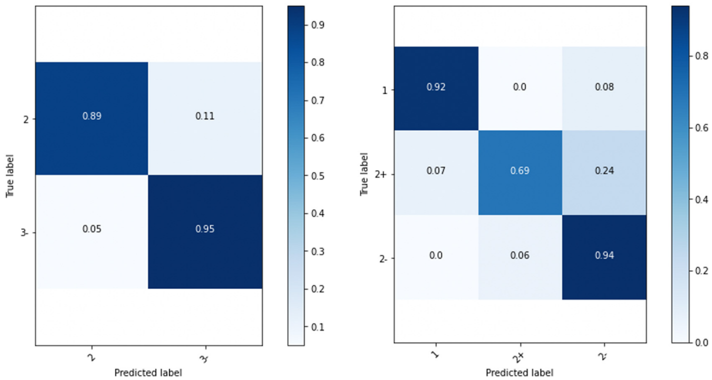

Fig. 6. Confusion matrices of quality classification task of HUVGG-16: Left: “Raffaello” series [codes 3,4]; right: “Montefeltro” series [codes 10,11].

8 Conclusions

Today the QC on the various types of shotgun stocks is mainly based on the evaluation of the human eye, following that the results are affected by a high inter and intra-subject variability. The introduction of DL, based on VGG-16 and ordinal categorical cross-entropy loss, for the automation of aesthetic QC of wooden stock, has been proven to be effective in order to automatize and standardize the overall QC process. The integration of the trained network in the QC platform, allows the reduction of QC timing from minutes to tenths of a second, allowing substantially faster business productivity and eliminating bottlenecks in business processes. The deep understanding of the overall procedure and the strict collaboration with the company lead to detect and avoid an unwanted bias in the QC classification procedure. The analysis confirms how the presence of bias in the dataset and in the learning procedure could be a disruptive finding that may lead to an overestimation of the performance. The proposed HUVGG-16 solution based on hierarchical networks allows to mitigate the detected bias by learning the characteristics that properly describe the quality of shotgun, rather than other confound characteristics. Taking into account that the DL model should focus on the wood part we are currently considering the inclusion of a segmentation step prior the classification of gradining. Additionally, we are currently testing the generalization power of the proposed DL approach in a different company's production chain for supporting the QC process of the technician in a different environment and operating condition. Future work may also be addressed to integrate the proposed approach into a QC serverless platform where the predicted quality class is obtained by ingestion event. The technician may trigger a cloud function that could invoke the DL model to provide the inference. This setting may ensure the high scalability of the system while allowing the continuous fine-tuning of the DL model based on the new input available.

Our work aims to propose a deep learning approach, specifically tailored for providing the aesthetic quality classification of shotguns based on the analysis of wood grains without running into an unwanted bias. The higher performance obtained by the proposed HUVGG-16 approach for quality class prediction suggests how the proposed approach represents a solution for automatizing the overall QC procedure in a challenging industrial case scenario and a proof of concept for detecting and mitigated unwanted bias.

Acknowledgments. This work was supported within the research agreement between Università Politecnica delle Marche and Benelli Armi Spa.

References

1. Internet trolls turn a computer into a nazi. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing. Accessed 02 July 2020
2. Bai, Y., Li, C., Sun, Z., Chen, H.: Deep neural network for manufacturing quality prediction. In: 2017 Prognostics and System Health Management Conference (PHM-Harbin), pp. 1–5 (2017)
3. Basu, S., et al.: Deep neural networks for texture classification–a theoretical analysis. Neural Netw. **97**, 173–182 (2018)
4. Usuga Cadavid, J.P., Lamouri, S., Grabot, B., Pellerin, R., Fortin, A.: Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. J. Intell. Manufact. **31**(6), 1531–1558 (2020). https://doi.org/10.1007/s10845-019-01531-7
5. Calabrese, M., et al.: Sophia: an event-based iot and machine learning architecture for predictive maintenance in industry 4.0. Information **11**(4), 202 (2020)

6. Dai, W., Yoshigoe, K., Parsley, W.: Improving data quality through deep learning and statistical models. In: Latifi, S. (ed.) Information Technology - New Generations. AISC, vol. 558, pp. 515–522. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-54978-1_66
7. Escobar, C.A., Morales-Menendez, R.: Machine learning techniques for quality control in high conformance manufacturing environment. Adv. Mech. Eng. **10**(2), 1687814018755519 (2018). https://doi.org/10.1177/1687814018755519
8. Francis, J., Bian, L.: Deep learning for distortion prediction in laser-basedadditive manufacturing using big data. Manufact. Lett. **20**, 10–14 (2019). https://doi.org/10.1016/j.mfglet.2019.02.001,http://www.sciencedirect.com/science/article/pii/S221384631830172X
9. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)
10. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097–1105 (2012)
11. Muniategui, A., de la Yedra, A.G., del Barrio, J.A., Masenlle, M., Angulo, X., Moreno, R.: Mass production quality control of welds based on image processing and deep learning in safety components industry. In: Cudel, C., Bazeille, S., Verrier, N. (eds.) Fourteenth International Conference on Quality Control by Artificial Vision, vol. 11172, pp. 148–155. International Society for Optics and Photonics, SPIE (2019)
12. Ozdemir, R., Koc, M.: A quality control application on a smart factory prototype using deep learning methods. In: 2019 IEEE 14th International Conference on Computer Sciences and Information Technologies (CSIT) vol. 1, pp. 46–49 (2019)
13. Romeo, L., Loncarski, J., Paolanti, M., Bocchini, G., Mancini, A., Frontoni, E.: Machine learning-based design support system for the prediction of heterogeneous machine parameters in industry 4.0. Expert Syst. Appl. **140**, 112869 (2020). https://doi.org/10.1016/j.eswa.2019.112869, http://www.sciencedirect.com/science/article/pii/S0957417419305792
14. Sakib, N., Wuest, T.: Challenges and opportunities of condition-based predictive maintenance: a review. Procedia CIRP **78**, 267–272 (2018)
15. Selvaraju, R.R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., Batra, D.: Grad-cam: visual explanations from deep networks via gradient-based localization. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 618–626 (2017)
16. Simon, P., Uma, V.: Deep learning based feature extraction for texture classification. Procedia Comput. Sci. **171**, 1680–1687 (2020)
17. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014)
18. Villalba-Diez, J., Schmidt, D., Gevers, R., Ordieres-Meré, J., Buchwitz, M., Wellbrock, W.: Deep learning for industrial computer vision quality control in the printing industry 4.0. Sensors **19**(18), 3987 (2019). https://doi.org/10.3390/s19183987
19. Wang, T., Chen, Y., Qiao, M., Snoussi, H.: A fast and robust convolutional neural network-based defect detection model in product quality control. Int. J. Adv. Manufact. Technol. **94**(9–12), 3465–3471 (2018)