THE ANNALS OF "DUNAREA DE JOS" UNIVERSITY OF GALATI
FASCICLE IX. METALLURGY AND MATERIALS SCIENCE
N°. 4 - 2023, ISSN 2668-4748; e-ISSN 2668-4756
Article DOI: https://doi.org/10.35219/mms.2023.4.15

SUPERVISED LEARNING PLASTIC DEFECT ALGORITHM DETECTION

Florin Bogdan MARIN, Mihaela MARIN
"Dunarea de Jos" University of Galati, Romania
e-mail: florin.marin@ugal.ro, mihaela.marin@ugal.ro

ABSTRACT

The goal of this research is to develop a supervised learning algorithm able to detect the defects of plastic's material. Finding patterns or examples in a dataset that differ from the norm is known as anomaly detection in plastic textures. Anomalies, in the context of plastic textures, can refer to imperfections' deviations, or anomalies in the material that may have an impact on the final product's overall quality. Conventional anomaly detection techniques frequently rely on rule-based systems or manual examination, which can be laborious, subjective, and unable to identify small anomalies.

KEYWORDS: computer vision, passenger fatigue detection, Advanced Driver Assistance System

1. Introduction

In recent years, the proliferation of plastic materials in various industries has raised concerns about the need for effective quality control and anomaly detection in the production process. Ensuring the quality and integrity of plastic textures is crucial for maintaining product standards and meeting consumer expectations.

The importance of product enclosure plastic components extends far beyond their structural role, encompassing crucial aspects that directly impact the user experience and satisfaction of clients. Two significant facets that contribute to this importance are the touch texture and design of these plastic components, touch texture and design [1].

The touch texture of plastic components plays a pivotal role in shaping the tactile experience of users interacting with a product. Clients often form their first impressions through the sense of touch, and the texture of plastic enclosures can greatly influence the perceived quality and premium feel of a product. A smooth and pleasing texture not only enhances the overall aesthetics but also conveys a sense of durability and sophistication [2].

The design of product enclosure plastic components is a key factor in determining the visual appeal and functionality of a product. A good design not only contributes to the product's aesthetic appeal but also influences its usability and ergonomics. Clients often seek products that not only perform their intended functions efficiently but also align with their personal preferences and lifestyle. The design of plastic components can significantly impact the user's overall satisfaction and willingness to engage with the product. Additionally, an aesthetically pleasing design enhances the marketability of the product, attracting potential customers and setting it apart from competitors. Thus, the design of plastic components within the product enclosure is integral to creating a holistic and desirable user experience.

One promising approach to address this challenge is supervised anomaly detection using transfer learning, a technique that leverages pre-trained models to enhance the performance of anomaly detection in specific domains.

Anomaly detection in plastic textures involves identifying patterns or instances that deviate from the norm within a given dataset. In the context of plastic textures, anomalies may include defects, irregularities, or abnormalities in the material that can affect the overall quality of the final product. Traditional anomaly detection methods often rely on manual inspection or rule-based systems, which can be time-consuming, subjective, and may not capture subtle anomalies.

Supervised learning is a machine learning paradigm where a model is trained on labelled data to make predictions or classifications [3, 4]. Transfer learning extends this concept by leveraging knowledge gained from pre-trained models on large datasets and applying it to a new, related task. In the context of plastic texture anomaly detection, transfer

THE ANNALS OF "DUNAREA DE JOS" UNIVERSITY OF GALATI
FASCICLE IX. METALLURGY AND MATERIALS SCIENCE
N°. 4 - 2023, ISSN 2668-4748; e-ISSN 2668-4756
Article DOI: https://doi.org/10.35219/mms.2023.4.15

learning allows the model to benefit from patterns learned from diverse datasets, improving its ability to identify anomalies in specific plastic textures [5, 6].

There are many challenges in plastic texture anomaly detection [7]. Plastic textures exhibit a wide range of variations, making it challenging to develop a one-size-fits-all anomaly detection model [1, 8, 9-10]. Supervised learning may struggle when confronted with limited labelled data, as collecting a comprehensive dataset for every type of plastic texture anomaly is often impractical (Fig. 1). Transfer learning addresses this challenge by enabling the model to generalize well to new data by leveraging knowledge from broader domains. Transfer learning enables the model to extract relevant features from pre-trained models, which is particularly beneficial in cases where manual feature engineering is challenging.

Improved generalization is necessary because by learning from diverse datasets, the model can better generalize to various plastic textures, even those with limited labelled data, thereby enhancing its anomaly detection capabilities [11, 12]. Leveraging pre-trained models significantly reduces the time required for model training, allowing for more efficient development and deployment of anomaly detection systems. As the plastic industry evolves, new types of anomalies may emerge [13]. Transfer learning equips the model to adapt to these changes by incorporating knowledge from continuously updated pre-trained models [14].

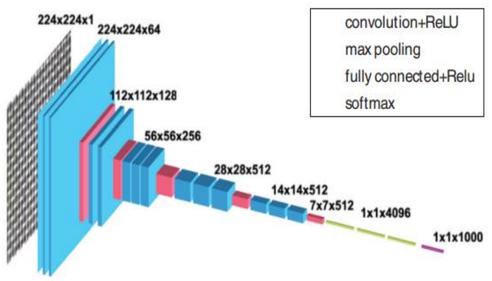

Fig. 1. *Architecture of the VGG19 network* [3]

Supervised anomaly detection using transfer learning presents a promising avenue for enhancing the detection of anomalies in plastic textures [15, 16]. By leveraging the power of pre-trained models and transferring knowledge across domains, this approach addresses the challenges posed by the diverse and evolving nature of plastic materials. As industries continue to prioritize quality control, the integration of transfer learning in anomaly detection systems holds great potential for ensuring the production of high-quality plastic products that meet the stringent demands of today's markets.

2. Technique proposed

Supervised anomaly detection in computer vision for detecting plastic texture defects often involves the use of deep learning algorithms. One commonly employed architecture for this task is the Convolutional Neural Network (CNN), which has proven effective in image classification and anomaly detection. Here is an outline of the architecture for supervised anomaly detection in the context of plastic texture defect detection.

We used several steps to identify defect in texture of plastic material. We used a pre-trained CNN architecture with ResNet. The supervised training is consisting of adding new layers to the modified CNN for the specific anomaly detection task.

We trained the model on the labelled dataset, using a binary cross-entropy loss function to distinguish between normal and defective textures. We used 200 images of samples with no defects and 40 with defects. During testing, pass new images through the trained model to obtain anomaly scores. The plastic component is of a hardware portable enclosure (Fig. 2).

Fig. 2. *Plastic enclosure pattern real size*

Anomaly scores can be calculated based on the difference between the predicted output and the ground truth labels.

Higher anomaly scores indicate a higher likelihood of a defect. To evaluate the performance of the model on a separate test dataset we used 20 with defects.

Fine-tune the model and adjust hyperparameters as needed for optimal performance is needed during using to introduce new data to the model.

Iterating on the model based on the evaluation results and, if necessary, incorporate additional data for further training is a must. We excluded techniques such as data augmentation to enhance the model's ability to generalize to different defect types, as will affect precision.

THE ANNALS OF “DUNAREA DE JOS” UNIVERSITY OF GALATI
FASCICLE IX. METALLURGY AND MATERIALS SCIENCE
N°. 4 - 2023, ISSN 2668-4748; e-ISSN 2668-4756
Article DOI: https://doi.org/10.35219/mms.2023.4.15

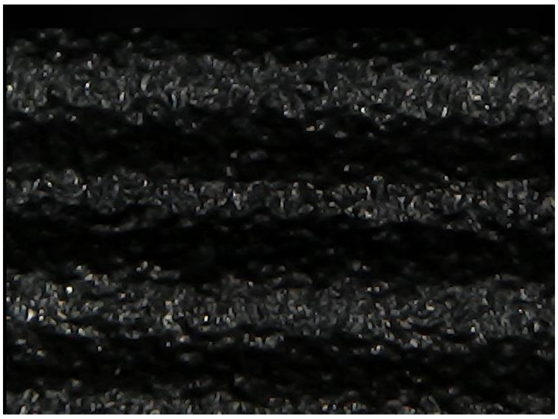

Fig. 3. *Pattern at 50X magnification*

As it may be noted the image at 50X magnification shows that no constant features can be detected such as lines. The pattern in the plastic enclosure exists but no direct detection using patterns of constant information can be used (Fig. 3 and Fig. 4). This algorithm provides a framework for implementing supervised anomaly detection in computer vision for plastic texture defect detection. We underline that the choice of the pre-trained model, architecture modifications and hyperparameter tuning may vary based on the specific plastic textures. Accuracy learning rate shows a good learning rate though overfitting shows that the trained samples need more data for training. We used a network with 4 hidden layers, the input images are 128 X 128 pixels. We choose high learning rate (0.01) and we can see the model oscillate (Fig. 5). We chose too low a learning rate (0.001) but we obtained little or no convergence. Finally, we obtained a 93% rate detection.

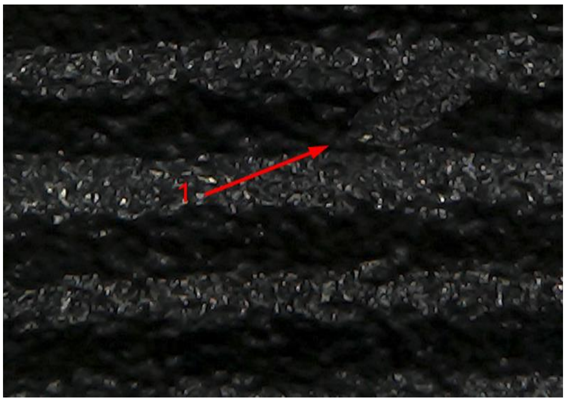

Fig. 4. *Defect present (1)*

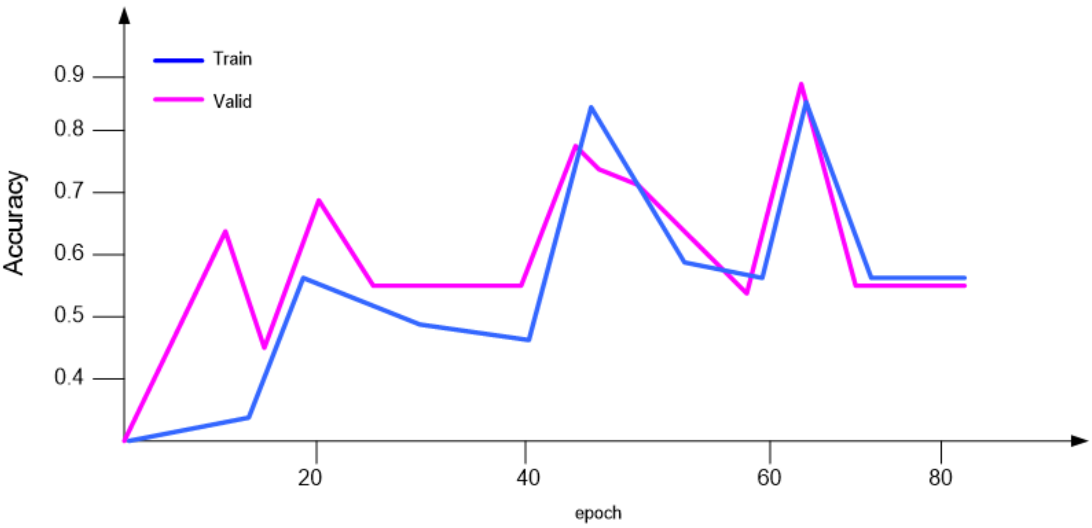

Fig. 5. *Accuracy learning rate*

3. Conclusions

Detecting defects in plastic enclosure is a challenging task when the patterns show hard to find patterns. Moreover, in case of images at magnification, the identification needs to be with high precision rate. The detection of defects allows to take measures to identify the source of defects.

The parameters of the network are causing the accuracy.

For our experiments choosing a high learning rate for Adam optimization parameter allows identification of defects. Also, the resolution of images for training translates into improved detection rate.

References

[1]. Ai D., Jiang G., Siew Kei L., Li C., *Automatic Pixel-Level Pavement Crack Detection Using Information of Multi-Scale Neighborhoods*, IEEE Access, vol. 6, p. 24452-24463, 2018.

[2]. Yao H., Liu Y., Li X., You Z., Feng Y., Lu W., *A Detection Method for Pavement Cracks Combining Object Detection and Attention Mechanism*, IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, p. 22179-22189, Nov. 2022.

[3]. Velasquez R. A., Vanessa J., Lara M., *Automatic evaluation of cracks with semantic segmentation model with U-Net and an Efficient Net-b*, IEEE XXX International Conference on Electronics, Electrical Engineering and Computing (INTERCON), p. 1-7, 2023.

[4]. Dinh T. H. *et al.*, *Toward Vision-Based Concrete Crack Detection: Automatic Simulation of Real-World Cracks*, EEE Transactions on Instrumentation and Measurement, vol. 72, p. 1-15, art no. 5032015, 2023.

[5]. Park J., Chen Y. -C., Li Y. -J., Kitani K., *Crack Detection and Refinement Via Deep Reinforcement Learning*, IEEE International Conference on Image Processing (ICIP), Anchorage, AK, USA, 2021.

[6]. Akcay S., Abarghouei A. A., Breckon T. P., *GANomaly: Semi-supervised anomaly detection via adversarial training*, 2018.

[7]. Antipov G., Berrani S.-A., Ruchaud N., Dugelay J.-L., *Learned vs. hand-crafted features for pedestrian gender recognition*, Proceedings of the 23rd ACM International Conference on Multimedia, 2015.

[8]. Zhang J., Liang J., Zhang C., Zhao H., *Scale invariant texture representation based on frequency decomposition and gradient orientation*, Pattern Recognition Letters, vol. 51, p. 57-62, 2015.

[9]. Perepu P. K., *Deep learning for detection of text polarity in natural scene images*, Neurocomputing, vol. 431, 2021.

[10]. Zhu A., Wang G., Dong Y., *Detecting natural scenes text via auto image partition, two-stage grouping and two-layer classification*, Pattern Recognition Letters, vol. 67, Part 2, p. 153-162, 2015.

[11]. Do M. N., Vetterli M., *Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Leibler distance*, IEEE Transactions on Image Processing, vol. 11, no. 2, p. 146-158, 2002.

[12]. Mathiassen J., Skavhaug A., Bo K., *Texture Similarity Measure Using Kullback-Leibler Divergence between Gamma Distributions*, ECCV 2002, LNCS 2352, p. 133-147, 2002.

[13]. Aiger D., Talbot H., *The phase only transform for unsupervised surface defect detection*, IEEE Computer Society Conference on Computer Vision and Pattern Recognition, p. 295-302, 2010.

[14]. Arivazhag S., Ganesan L., Bama S., *Fault segmentation in fabric images using Gabor wavelet transform*, Mach. Vis. Appl., vol. 16, p. 356-363, 2006.

[15]. Badrinarayanan V., Kendall A., Cipolla R., *Segnet: A deep convolutional encoder-decoder architecture for image segmentation*, IEEE transactions on pattern analysis and machine intelligence, 2017.

[16]. Maalej M., Cherif R., Yaddaden Y., Khoumsi A., *Automatic Crack Detection on Concrete Structure Using a Deep Convolutional Neural Network and Transfer Learning*, 2nd International Conference on Advanced Electrical Engineering (ICAEE), p. 1-6, 2022.