aurum

AURUM MÜHENDİSLİK SİSTEMLERİ VE MİMARLIK DERGİSİ
AURUM JOURNAL OF ENGINEERING SYSTEMS AND ARCHITECTURE

Cilt 7, Sayı 2 | Kış 2023
Volume 7, No 2 | Winter 2023

BROKEN STITCH DETECTION METHOD FOR SEWING OPERATION USING CNN FEATURE MAP AND IMAGE-PROCESSING TECHNIQUES

Samah Noaman Sahi SAHI [1*], Timur İNAN[2]

[1]Department of İnformation Technology, Faculty of Engineering, Altinbas University, Istanbul,Turkey
203721033@ogr.altinbas.edu.tr (https://orcid.org/0009-0001-9238-8289)

[2]Department of İnformation Technology, Faculty of Engineering, Altinbas University, Istanbul,Turkey
timur.inan@altinbas.edu.tr, (https://orcid.org/0000-0002-6647-3025)

Received: 11.10.2023
Accepted: 27.10.2023
Published: 31.12.2023
*Corresponding author

Research Article
pp.217-233
DOI: 10.53600/ajesa.1374410

Abstract

Quality in industrial processes has become increasingly important and cost reduction and process optimization are becoming increasingly necessary Quality control brings increased production and even increased profits for a process. It can be said, then, that it is the most important metric when it comes to production. It is extremely difficult to have a 100% defect-free manufacturing process. One of the industrial processes that has received such attention regarding defects is the weaving process. The present work will make a global study on Machine Learning techniques and also on Wavelets. This study may serve as a basis for future academic work. The application built in the present work will also serve as an example of how a computer vision system can vary from the classifier algorithm used to the feature extraction technique, which in this case, will use the Wavelet Transform. In this work, we Survey the state of the art in methods of recognizing defects in fabrics. We will also Create the database, as well as the set of images to be used. Extract information from the image with the Wavelet Transform. Test different classification algorithms in order to find the best answer for this problem. Improve the performance of the classifier algorithms through the CNN algorithm. Validate the system using the k-fold cross-validation technique.

Keywords: CNN, DL, ML, WT.

CNN ÖZELLİK HARİTASI VE GÖRÜNTÜ İŞLEME TEKNİKLERİNİ KULLANARAK DİKİŞ İŞLEMİNDE KIRIK DİKİŞ TESPİT YÖNTEMİ

Özet

Endüstriyel süreçlerde kalite giderek daha önemli hale geliyor ve maliyetlerin düşürülmesi ve süreç optimizasyonu giderek daha gerekli hale geliyor. Kalite kontrolü, bir süreç için artan üretim ve hatta artan kar sağlar. O halde üretim söz konusu olduğunda en önemli ölçüt olduğu söylenebilir. %100 hatasız bir üretim sürecine sahip olmak son derece zordur. Kusurlar açısından bu kadar ilgi gören endüstriyel süreçlerden biri de dokuma işlemidir. Bu çalışma, Makine Öğrenimi teknikleri ve ayrıca Dalgacıklar üzerine küresel bir çalışma yapacaktır. Bu çalışma gelecekte yapılacak akademik çalışmalara temel teşkil edebilir. Mevcut çalışmada oluşturulan uygulama aynı zamanda bir bilgisayarlı görme sisteminin, kullanılan sınıflandırıcı algoritmasından, bu durumda Dalgacık Dönüşümünü kullanacak olan özellik çıkarma tekniğine kadar nasıl değişebileceğinin bir örneği olarak hizmet edecektir. Bu çalışmada kumaşlardaki kusurları tespit etme yöntemlerinde en son teknolojiyi araştırıyoruz. Ayrıca veritabanını ve kullanılacak görsel setini de oluşturacağız. Dalgacık Dönüşümü ile görüntüden bilgi çıkarın. Bu soruna en iyi cevabı bulmak için farklı sınıflandırma algoritmalarını test edin. CNN algoritması aracılığıyla sınıflandırıcı algoritmaların performansını artırın. K-katlı çapraz doğrulama tekniğini kullanarak sistemi doğrulayın.

Anahtar Kelimeler: CNN, DL, ML, WT.

1. Introduction

manufacturing defects. The textile industry is an important sector of the Turkish and world economy. The primary purpose of fabrics is to dress and protect the human body. For this and other reasons, manufacturing quality is the subject of numerous works (Thoben, Wiesner, & Wuest, 2017; Xu, Cao, Zhou, & Gao, 2020)Two factors are important in weaving a fabric. Firstly, the speed of the loom, which directly impacts productivity and, consequently, the company's revenue. On the other hand, quality is also an important factor. According to [5]), the price of a defective fabric reduces about 45% to 65% of the sale value. There are first and second quality fabrics according to (Hu, 2011)Discernible defects with various disparities in physical size and shape inevitably reside on the fabric surface during the textile production process due to reasons such as machine failure, damage, and pollution, consequently negatively compromising the price realization capabilities of completed items. (Liu, Lee, & Lee, 2020). While manual detection can be used to identify non-conforming products, it is unreliable due to workers' inattention and poor visual judgment, with an accuracy of just 60-75%. (Liu et al., 2020). To overcome such difficulties, innovative algorithms and approaches for automating fabric detection have been developed in recent decades with astounding results (Thoben et al., 2017; Yan, Liu, Xiang, & Jin, 2020). Despite rising industrial and academic concerns, automatic detection technology for fabric faults is a recurring issue in the pursuit of efficiency in the modern textile industry.

The automatic defect detection approach can be divided into two categories based on the feature extraction strategy: classical and deep learning. Traditional approaches are often based on artificially manufactured features that are intended to mimic textural flaws. It is further subdivided into four subcategories (Hu, 2011), including spectral, statistical, structural, and model-based techniques. While these conventional methods can provide satisfactory results in certain product categories, current production necessitates the management of complex and varied picture texture patterns in conjunction with the help of appropriate hardware equipment and a production environment. In most cases, established procedures are difficult to generalize in new operating contexts and integrate into new designs.

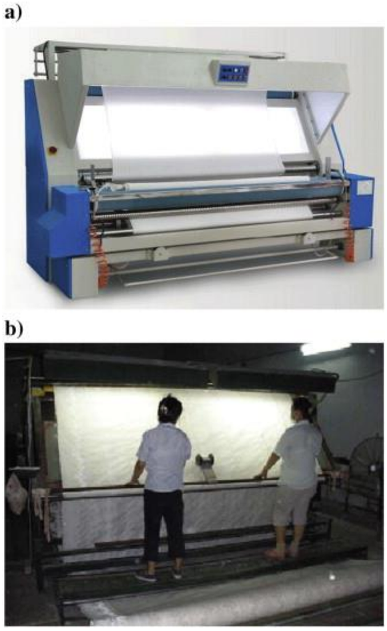

Figure 1: Fabric defect detection machine.

This shows the bottleneck that exists in terms of productivity. Not to mention the countless other problems that the human visual system can encounter, one of which is inspector fatigue. The process of inspection and detection of defects in fabrics is carried out by specialized people The way the material is evaluated varies between factories some, the workers themselves place the fabric on the table for verification. However, most have automated ways of taking the roll out of the weaving machine in a motorized way and unwinding it in a controlled lighting environment. The inspection is carried out at a relatively high speed, between 8 and 20 meters per minute Figure 2 shows better how the inspection is carried out by a specialist in the production of a factory.

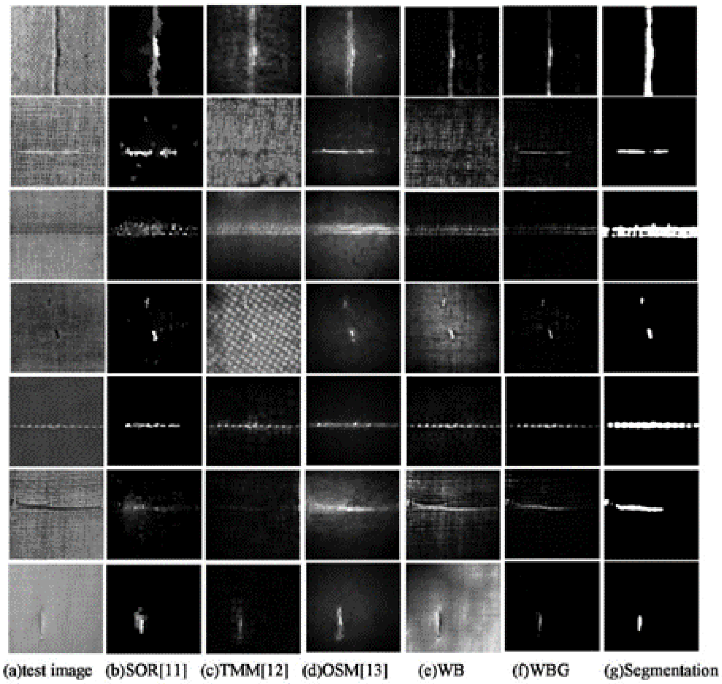

Figure :2 Example of fabric defects (Thoben et al., 2017).

As human error can happen for several reasons, such as, for example, exhaustion, a computer system capable of performing this recognition role is necessary. Artificial intelligence is an ancient field within computing. In the past, these algorithms were treated only theoretically, and no great applications and possibilities were seen. Today, with the increase in the number of problems and the increase in devices that somehow perform data acquisition, these algorithms have become increasingly important. One area that has stood out a lot in recent years is Machine Learning. Machine Learning is the process of inducing a hypothesis (or function approximation) from past experience. Thus, the union of two great techniques, machine learning and image processing, become a powerful tool in solving problems of the type that this work addresses. There are countless jobs and areas in which these two techniques are used to solve a given problem.

2. Fabrid Defect Detectıon Algorıthms

2.1. Statistics Algorithms

(Habib, Shuvo, Uddin, & Ahmed, 2016) Gray-level co-occurrence matrices (GLCM), autocorrelation analysis, and fractal dimension features are examples of statistical approaches that use the geographic distribution of gray values in photographs. Raheja et al. provide an automated GLCM-based method for detecting fabric defects. This approach is outlined in their research. In this technique, the interpixel distance and GLMC statistics are used to generate a signal graph. (A flawed image and a flawless image are compared with a test image. A Gabor filter-based approach was also used, which led to the identification of the research's flaws. It has been shown that GLCM-based algorithms enhance detection accuracy while requiring less complex processing (Raheja, Ajay, & Chaudhary, 2013; Raheja, Kumar, & Chaudhary, 2013).

(Anandan & Sabeenian, 2018) simplify the procedure of finding fabric defect characteristics by obtaining the related eigenvector. For instance, compared to strategies based on GLCM and wavelets, the performance of the provided method is higher. Kumar et al. (Kumar & Hafedh, 2013)have devised a statistical technique for detecting fabric flaws that use eigenvalues. The coefficient of variation may be used to identify photos of defective fabric images. According to the outcomes of the research's experimental procedures (this approach is straightforward and easy to apply).

(Li et al., 2021)compute the membership degree of each segment of the fabric in order to facilitate the detection of flaws. By combining the attributes of the membership function area with the image's extreme point density map, it may be possible to determine which image regions are most crucial for detecting defect kinds. In addition, the whole system employs threshold processing and morphological processing.

The author of this method claims that it can identify fabric faults precisely and efficiently, despite interference from background noise and texture.

(Ben Gharsallah & Ben Braiek, 2021), an enhanced anisotropic diffusion filter and saliency image qualities have the potential to be used in the process of finding fabric defects. Due to the inability of typical approaches for anisotropic diffusion to distinguish the defect edge from the background texture, the improved methodology for anisotropic diffusion integrates both the local gradient magnitude and a saliency map. This distinguishes the defect's edge from the backdrop texture. Using this method, it is feasible to eliminate the texture backdrop without difficulty; but, the picture fault edge will remain. The following is a quick overview of the statistical methods that may be used to find flaws in textiles.

The automatic defect detection approach can be divided into two categories based on the feature extraction strategy: classical and deep learning. Traditional approaches are often based on artificially manufactured features that are intended to mimic textural flaws. It is further subdivided into four subcategories (Hu, 2011), including spectral, statistical, structural, and model-based techniques. While these conventional methods can provide satisfactory results in certain product categories, current production necessitates the management of complex and varied picture texture patterns in conjunction with the help of appropriate hardware equipment and a production environment. In most cases, established procedures are difficult to generalize in new operating contexts and integrate into new designs, (Ngan, Pang, & Yung, 2011). Furthermore, Jia et al. suggested a number of defect identification algorithms based on lattice segmentation (Ben Gharsallah & Ben Braiek, 2021; Kumar & Hafedh, 2013), with the goal of reducing fabric defect detection to a problem of estimating lattice similarity. However, picture periodic pattern analysis based on computer approaches often demands strong stationarity and low pattern period complexity. Furthermore, an unsolvable problem with these works is communication failure between image sections caused by lattice segmentation. As a result, depending on comparisons between small areas may overlook the oddity of the image as a whole.

2.2. Statistics Algorithms

Spectral approaches include transforms such as the Fourier transform, the Gabor transform, the wavelet transform, and the discrete cosine transform (Chetverikov & Hanbury, 2002). The Fourier transform, the wavelet transforms, and the Gabor transform have all been extensively studied and evaluated for their possible use in the identification of fabric defects. (Yan et al., 2020) offer an automated method for recognizing fabric flaws that employs a multiscale wavelet transform and a Gaussian mixture model. After decomposing the image using the Pyramid wavelet transform, we reconstructed an image of textile fabric using the thresholding approach. The rebuilt picture was then segmented using the Gaussian mixture model. Experiments have shown that the suggested classification and categorization scheme for incorrect photos is successful.

(Thoben et al., 2017) use information on the fabric's local homogeneity and the discrete cosine transform to identify fabric defects (DCT). The newly computed homogeneity picture was DCT-processed, and the distinct energy characteristics of each DCT block were retrieved when processing was complete. Following this, the feedforward neural networks classifier is used to the data to identify the retrieved attributes.

2.3. Methodology of Structural Organization

The golden image subtraction (GIS) approach is an exceptional technique for segmenting problem spots on an image of patterned textile fabric. (Thoben et al., 2017) recommended using the wavelet-preprocessed golden image removal approach (WGIS). In addition, this research evaluated the efficacy of wavelet transforms, GIS, and the suggested WGIS methodology, concluding that the WGIS technique performed the best.

used a similarity measure in the feature space to evaluate the similarity of nonoverlapping fabric picture parts. This was accomplished by comparing the photos. When applied to image datasets including box and star pattern combinations, the Isotropic Lattice Segmentation (ILS) approach yields positive results.

In a subsequent work, (Bullon, González Arrieta, Hernández Encinas, & Queiruga Dios, 2017)introduced a novel approach based on lattice segmentation and lattice templates (Sibly Sadik & Islam, 2014). We are considering the idea of segmenting lattices based on the placement criteria specified by the various texture primitive classes on the lattices. When the distance between the indeterminate lattice and the lattice template exceeds a particular threshold, lattices are judged faulty. Incorporating template data gleaned from defect-free images into the method allowed for its further enhancement.

2.4. Model-Based Methodologies

The themes described by Ngan and others may be used to identify flaws in the material. According to this procedure, lattice and motif designs may be deconstructed into their constituent lattices and motifs. Using moving subtraction (Liu et al., 2020), more energy is acquired to discriminate between regions with defects and regions without flaws. In order to reduce the frequency of false positives and false negatives, a Gaussian mixture model is used to represent the energy variance (Ben Gharsallah & Ben Braiek, 2021). The convex hull is produced inside an elliptical area that most closely fits the data for each cluster. Analyzing photographs of uniformly structured textiles is possible using a method developed by Lucia and colleagues. (e's two-step technique incorporates both the feature extraction and defect detection processes. Second, in the first phase, the Euclidean norm of the features is computed and utilized to identify any defects. The Gabor filter bank and main component analysis are used in the second step. Using the publicly available TILDA database, a patch-based strategy was constructed and assessed (Sayed, 2016).

devised a technique based on principal component analysis and nonlocal average filtering in order to improve the fabric texture and minimize noise in environmentally friendly textiles. This approach was used. In this case, an approach for evaluating faults based on texture is employed to evaluate the degree of similarity. As a direct result of this, it is able to distinguish between regions with and without defects. Certain members of the academic community see the issue of identifying faults in textiles as a one-class problem.

3. Proposed Model

A productivity bottleneck is then noted, given that a human inspector, when performing fully, can inspect about 20 meters per minute of a roll of fabric. Naturally, given the characteristics of the task, an automation of this process could not only increase productivity, but also reduce costs or free up human labor for other tasks. Therefore, the objective of this course completion work is to apply the machine learning concepts described here to solve a real problem: defect detection - as shown in Figure (1-3) in fabrics in a production line, beyond the classification of the detected print.

Figure : 3 Example of fabric with manufacturing defects.

To this end, the proposed model uses as input images of fabrics in production lines. The source of the images is the public dataset ZJU-Leaper , which contains more than 90 thousand images.

3.1. Synthesis and Characterization

Artificial neural networks are strongly inspired by the biological functioning of nervous systems. Input data is fed to a group of interconnected computational nodes called neurons, where each input X is multiplied by a weight ω and then summed over the other inputs and applied to the neuron's activation function. This function determines whether the neuron will "fire" or not, producing an output that will be fed to subsequent layers of the net. The operation of a neuron can be expressed in general terms by Equation 1, where f represents the activation function.

$$Output = f(\sum \omega i X i) \quad (1)$$

Activation functions determine if the neuron in question will be activated or not, besides being responsible for adding non-linearity to the model (since the weighted sum of inputs is purely linear). An example of a widely used activation function is ReLU [7](Rectified Linear Unit), which returns 0 for values less than or equal to zero and returns the input itself for values greater than 0. Figure 4 below represents the behavior of this activation function.

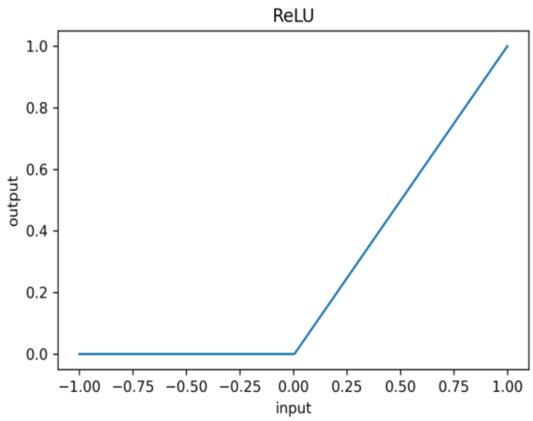

Figure 4: Behavior of the ReLU function.

Information, in order to speed up the computational process. The pooling process consists in representing an area of n x n pixels in a single pixel, and repeating this process for the whole image, sliding this "window" of dimension n x n . This representation can be done by averaging the numerical values or using the maximum among these values, for example.

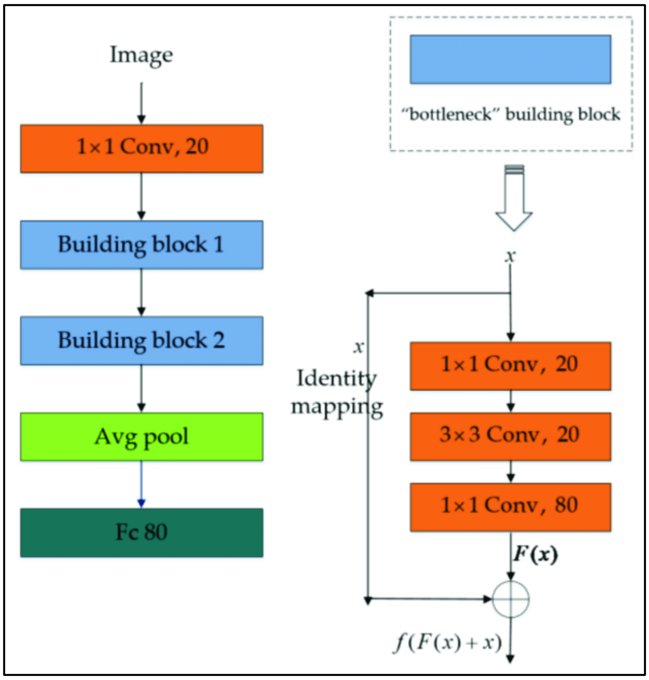

Figure 5: Visual representation of A resnet logic block.

One more relevant issue is that objects may appear in different scales in relation to the total image size. To improve performance for recognition systems a commonly used approach is the use of Feature Pyramids (Anandan & Sabeenian, 2018). This method consists of using a hierarchical pyramid of prediction regions, as illustrated in Figure 7. Each level of the pyramid has its weights adjusted separately, so that all levels are semantically strong. Outputs from the highest level, semantically stronger but spatially sparser, are then rescaled and merged with the output of the second hierarchical level of the pyramid through a lateral connection. This process is repeated until the dimensionality again becomes equal to the base of the pyramid. This process is more computationally costly and significantly increases the number of parameters, but when used in conjunction with CNNs it proves effective for recognizing objects at different scales.

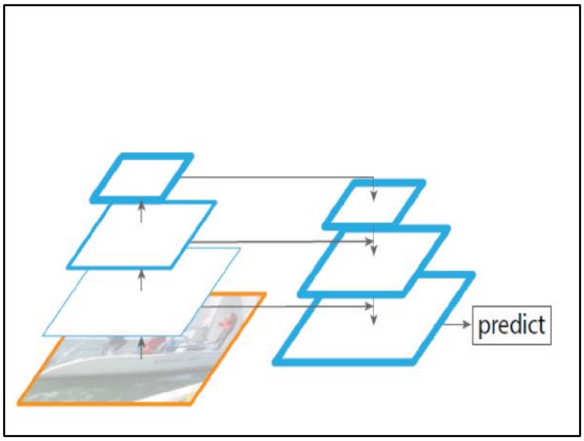

Figure 6: Visual representation of the characteristics pyramid.

Besides the quality of the architecture and size (number of neurons and layers) of the model itself, another determining factor in the performance of a deep learning algorithm is the quantity and quality of the data used for training, since it is from them that the model will learn.

One way to increase the amount of training data without collecting it is to use data augmentation, a method that generates new input data by applying certain transformations to them, such as horizontal and vertical flips, rotations, crops (clipping) of image sections, among others. Besides generating more data, this approach improves the model performance since a rotated or mirrored object remains the same object, however the numerical values of the pixels are different, helping the model to generalize.

Another way to improve model performance is to use transfer learning (Kumar & Hafedh, 2013), which consists of initializing the model already with weights from a training on another set of data, instead of zeros or random, and then doing the fine-tuning through a new model training on the new data. This process, in addition to speeding up training, produces better results and is more effective the greater the similarity between the current and previous training data sets.

3.2. Dataset

The dataset used was a ZJU-Leaper plot, which contains 98777 images of 512x512 pixels divided into 19 types of prints, with all classes containing defective examples. For the experiment, 756 images divided among 6 classes (prints) were used: plain white, thin stripes, thick stripes, dot, houndstooth and gingham. Of the 126 samples in each class, 72 samples were normal and 54 were defective. Figure 4.8 below shows some examples of prints with and without defects.

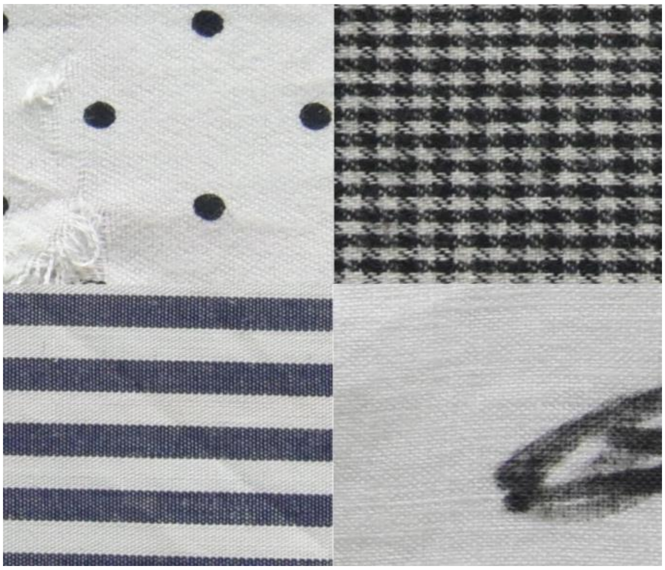

Figure 7: Examples of images present in ZJU-Leaper.

For computer vision tasks, annotations are critical for providing metadata to the model. In this context, annotations are a set of information (typically 4 positional coordinates of the bounding box and a label/class) that are used as ground truth (reference) by the model for learning. A bounding box is a rectangle aligned with the X and Y axes that describes the position of the object in the image.

The annotations were performed manually using the software CVAT (Computer Vision Annotation Tool) and following the following method: a bounding box comprising the whole image was annotated, with the class corresponding to the fabric print and a bounding box for each defect, when present, as a seventh class. Figure 4.9 below shows an example of annotation using this tool and method.

Cilt 7, Sayı 2 | Kış 2023
Volume 7, No 2 | Winter 2023

4. Results And Discussions

All 152 images in the validation set were classified correctly with respect to print, but a few predicted bounding boxes did not fill the entire image. This however does not have a real negative impact as these 6 classes are for classification only. Figure 4.10 shows an example of the expected output when no defects are present in the image.

Figure -8 Example of prediction without defects.

In the whole validation set there are 93 defects annotated in different images - this value is corresponding to Total No. of Positives The model detected 77 instances of the class "Defect" in the entire set (value corresponding to Positives Detected), of which 72 were considered "True Positives" since their IOU values were greater than 0.8. Table 1 below presents the metrics calculated from these values.

Table 1: Metrics of the model in the validation set.

Metric	Value
Accuracy	0,84
Recall	0,93
F1 Score	0,93

Reducing the IOU threshold for considering a detection as a True Positive to 0.5, the recall goes up to 1. This data shows that, as much as some defects were not detected, the false positive rate is very low.

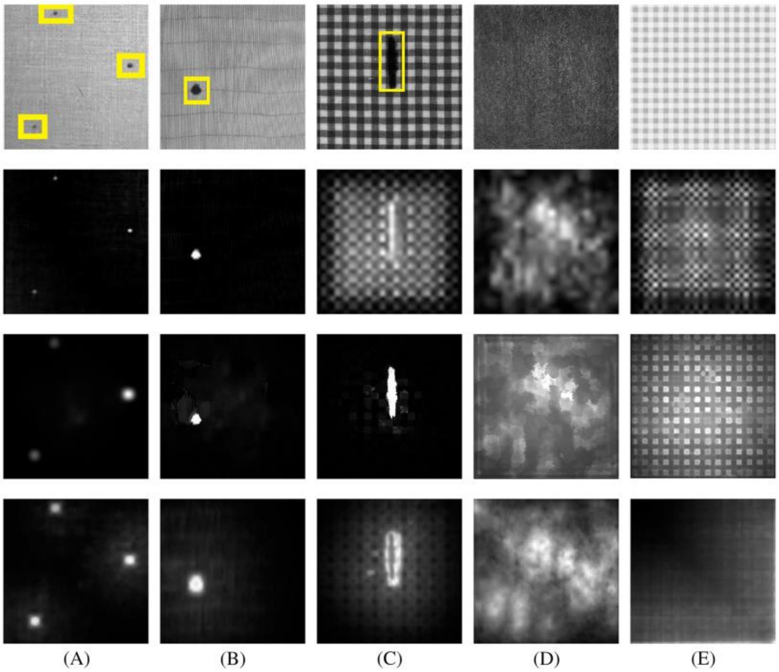

Figure 9: Example 1 of good prediction.

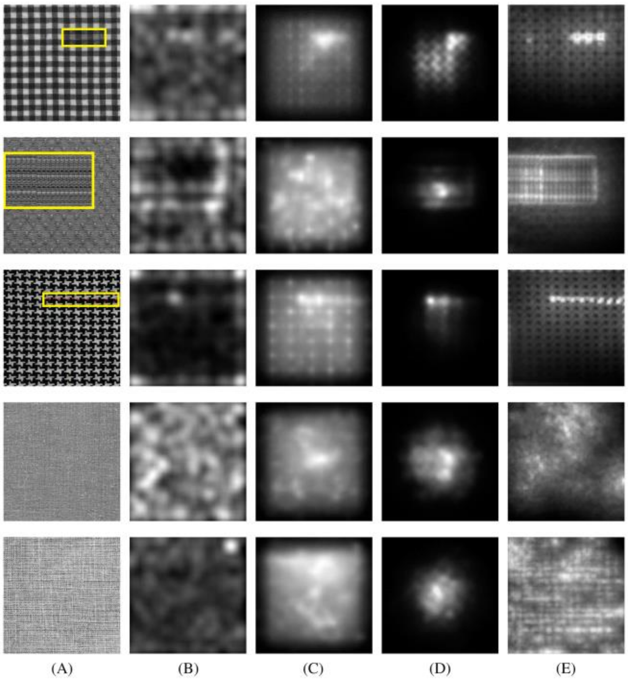

Figure 10: Example 2 of good prediction.

Among the related works, only provides the model accuracy values in the tested datasets (which is on average 87%), and it is not possible to calculate the F1 score because there is no information about the recall. Thus, Table 2 presents the comparison between the average F1 scores (among all classes/prints) of the related works in the validation set of their respective datasets.

Table 2: Comparison of F1 scores between the proposed model and related works.

Model	**F1 Score**
Jing et al.	0,92
FCSDA	0,53
RCT-MoGG	0,94
Mobile-Unet	0,91
RetinanetR (proposed)	0,95

The Detectron2 API also generates graphs of the mAPs over the model training iterations, as can be seen in

Figure 11. Even without a basis for comparison with other models, this data again indicates a very low false positive rate, given the AP 50 (mean average precision with the IOU threshold for true positives of 0.5) of 96.6% is even higher than the mAP (average across different thresholds) of 92.4%, indicating that some bounding boxes considered as false positives actually just did not cover the required defect area.

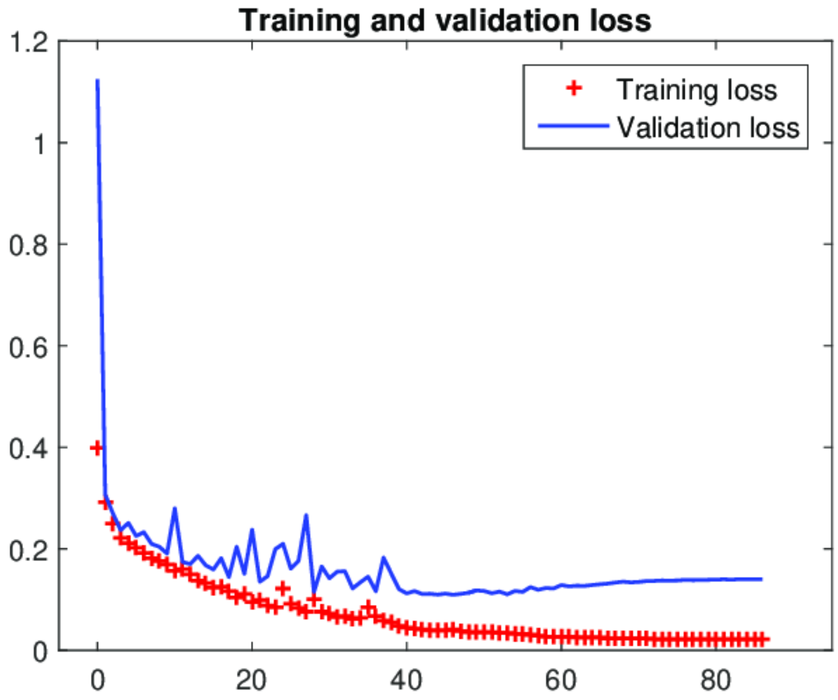

Figure 11: The training iterations of the proposed unet model.

The execution time for the prediction of the trained model was 19.07 seconds for the 152 images in the validation set using as hardware a personal computer with 16 Gb of RAM and using GPU (RTX 3060), which is equivalent to a rate of 8 images processed per second.

5. Conclusion And Future Work

The image is the visual representation of the real world perceived either by the eye or by an image acquisition device. The image is an important theme in human life especially with the technological progress that we are experiencing today. Indeed, the improvement of the image acquisition hardware comes within the framework of the improvement of the image quality that we wish to have and moreover justifies the importance of the image in our daily life. In addition, the importance of the image is also manifested in the integration of image sensors in several peripherals used on a daily basis such as webcams integrated into laptops, cameras in cell phones, etc. The image is used in different fields such as medicine, robotics, television, videoconferencing, CCTV, web and others. This important need for the image in everyday life has introduced new problems among which we can cite image compression, image search, segmentation, object extraction, organization and indexing of information on the web, etc. All these issues are essentially based on computer image processing or more generally the notion of machine learning. Indeed, when the use of a computer vision system can improve the fabric defect detection system in the industry.

References

Anandan, P., & Sabeenian, R. S. (2018). Fabric defect detection using discrete curvelet transform. Procedia computer science, 133, 1056-1065.

Ben Gharsallah, M., & Ben Braiek, E. (2021). A visual attention system based anisotropic diffusion method for an effective textile defect detection. The Journal of The Textile Institute, 112(12), 1925-1939.

Bullon, J., González Arrieta, M. A., Hernández Encinas, A., & Queiruga Dios, M. A. (2017). Manufacturing processes in the textile industry. Expert Systems for fabrics production.

Chetverikov, D., & Hanbury, A. (2002). Finding defects in texture using regularity and local orientation. Pattern Recognition, 35(10), 2165-2180.

Habib, M. T., Shuvo, S. B., Uddin, M. S., & Ahmed, F. (2016, December). Automated textile defect classification by Bayesian classifier based on statistical features. In 2016 International Workshop on Computational Intelligence (IWCI) (pp. 101-105). IEEE.

Hu, J. (Ed.). (2011). Computer technology for textiles and apparel. Elsevier.

Kumar, P. S., & Hafedh, H. (2013). Detection of defects in knitted fabric images using Eigen values. International Journal Computer Science Engineering-IJASCSE, 2(3), 7-10.

Li, C., Li, J., Li, Y., He, L., Fu, X., & Chen, J. (2021). Fabric defect detection in textile manufacturing: a survey of the state of the art. Security and Communication Networks, 2021, 1-13.

Liu, Y., Lee, J. M., & Lee, C. (2020). The challenges and opportunities of a global health crisis: the management and business implications of COVID-19 from an Asian perspective. Asian Business & Management, 19, 277-297.

Ngan, H. Y., Pang, G. K., & Yung, N. H. (2011). Automated fabric defect detection—A review. Image and vision computing, 29(7), 442-458.

Raheja, J. L., Ajay, B., & Chaudhary, A. (2013). Real time fabric defect detection system on an embedded DSP platform. Optik, 124(21), 5280-5284.

Raheja, J. L., Kumar, S., & Chaudhary, A. (2013). Fabric defect detection based on GLCM and Gabor filter: A comparison. Optik, 124(23), 6469-6474.

Sayed, M. S. (2016, October). Robust fabric defect detection algorithm using entropy filtering and minimum error thresholding. In 2016 IEEE 59th International Midwest Symposium on Circuits and Systems (MWSCAS) (pp. 1-4). IEEE.

Sibly Sadik, M., & Islam, S. (2014). Report on defects of woven fabrics and their remedies (Doctoral dissertation, Daffodil International University).

Thoben, K. D., Wiesner, S., & Wuest, T. (2017). “Industrie 4.0” and smart manufacturing-a review of research issues and application examples. International journal of automation technology, 11(1), 4-16.

Xu, X., Cao, D., Zhou, Y., & Gao, J. (2020). Application of neural network algorithm in fault diagnosis of mechanical intelligence. Mechanical Systems and Signal Processing, 141, 106625.

Yan, K., Liu, L., Xiang, Y., & Jin, Q. (2020). Guest editorial: AI and machine learning solution cyber intelligence technologies: new methodologies and applications. IEEE Transactions on Industrial Informatics, 16(10), 6626-6631.