Automatic fabric defect detection employing deep learning

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ABSTRACT

A major issue for fabric quality inspection is in the detection of defaults, it has become an extremely challenging goal for the textile industry to minimize costs in both production and quality inspection. The quality inspection is currently done manually by professionals; hence the need for the implementation of a fast, powerful, robust, and intelligent machine vision system in order to achieve high global quality, uniformity, and consistency of fabrics and to increase productivity. Consequently, the automatic inspection control process can improve productivity and enhance product quality. This article describes the approach used in developing a convolutional neural network for identifying fabric defects from input images of fabric surfaces. The proposed neural network is a pre-trained convolutional model 'DetectNet', it was adapted to be more efficient to the fabric image feature extraction. The developed model is capable of successfully distinguishing between defective fabric and non-defective with 93% accuracy for the first model and 96% for the second model.

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1. INTRODUCTION

With the fast progress of computer science and image processing technologies, computer vision technology has been applied largely in the textile industry. Consequently, the automatic inspection of fabric defect will become a self-evident solution to achieve high quality and lowest manpower prices [1]. Deep learning and computer vision have been largely used in textile fields, and numerous researches are available on this subject [2]–[7].

Deep learning is a leading machine learning technique which use artificial neural networks; it tends to be able to handle higher levels of abstracting data by using horizontal hierarchical architectures [8]. This approach is recent and has been largely used in many areas of artificial intelligence, such as health care, automotive industry, natural language processing, document analysis and recognition [9]–[12]. Deep neuron networks (DNNs) for image classification generally combine layers of convolutional neural networks (CNNs) and fully connected artificial neurons stacked to satisfy overlaying vision areas.

CNN is a category of deep learning and it is considered to be the leading classification system for image identification and classification problems. Instead of standard algorithms, CNNs are able to acquire advanced characteristics from the initial image without having to extract the specific features manually [13]. It has demonstrated an exceptional capacity in image treatment and categorization [2], [13]–[16].

The identification of fabric defects is of great interest to industrial and scientific researchers. The objective of identifying diverse anomalous designs in a complicated setting. Several approaches to identify defects under various hypotheses are available [17]–[22]. Abouelela *et al.* [20] supposed that the fabric structure is a composite of many basic shapes and determined that an area with dissimilar shapes was defective. Because there are relevant and significant dissimilarities between defective and non-defective structures over frequency spectrum, Chan [21] employed a Fourier transform to distinguish the defective and non-defective areas.

The deep learning approach has recently made an immense contribution to solving a wide number of computer vision challenges. Some methods [6], [23]–[26] implemented deep learning to identify defects in fabrics. On the basis of the trained and learned subdictionaries, Zhao *et al.* [26] developed a CNN model based on embedded short- and long-term visual storage for the classification of fabric images. The authors noted that the results show that deep learning methods conceived to solve a different classification task can be easily adapted to the problem of fabric fault classification, revealing the need for a well-conceived architecture. Although these methods have obtained good results in particular cases, most of them are restricted to the use of simple structures and are unable to deal with the real-world complexity of texture defect detection. In order to boost the efficiency of detecting fabric defects in the real world, a variety of important issues are required to be resolved. Firstly, labeling various real-world fabric faults is labor and required time. Due to the sophisticated variety of fabric and fault components, collecting a dataset of labelled data that spans all potential fabric textures is complicated and expensive. For example, when it comes to fabrics with unseen textures or materials, pre-trained detection models typically do not work well.

In this paper, the ability of DetectNet, a CNN, to detect fabric defects in the "Tilda" dataset was proposed to be evaluated in order to develop a reliable system capable of detecting defects in real time. This work is structured as such. An overview on the literature of fabric defect detection methods. Next, the proposed method for automatic defect detection is bounced, including dataset preparation and description of the proposed network model. The results and discussion are presented, and a conclusion is provided.

2. REVIEW OF PREVIOUS WORK

The majority of available literature on tissue investigation is primarily concerned with uniform textiles [27], [28], namely plain and woven fabrics. There are four principal classes of these methods that can be classified into: i) statistics approaches, ii) spectral approaches, iii) model-based approaches, and iv) learning-based approaches [28]. Among statistics approaches, the autocorrelation function and the co-occurrence matrix [29], [30] have been effectively used to detect the defects. Zhu *et al.* [28] used a combination of autocorrelation function and gray level co-occurrence matrix (GLCM) approaches to detecting defects in yarn-dyed fabrics. The autocorrelation function is used to specify a scale for the pattern images. GLCM is able to map image features, like contrast. However, such approaches are very labor-intensive.

Among the largely employed spectral approaches for defect detection are the Fourier transform [21], the wavelet transform [31], [32] and the Gabor filters [33]. Chan [21] applied Fourier transform to identify the structure fault of the tissue. To understand the behavior of the frequency spectrum, simulation techniques are used. A shortcoming when applying Fourier transform is that local data in the spatial region is not accessible and there is no tolerance for minor faults. As opposed to Fourier transform, Gabor filters and wavelet transform use spatial frequency analysis, which permits the identification of nearby imperfections. Ngan *et al.* [34] utilized the wavelet transform to consequently distinguish defaults on designed texture with a precision of 96.7%, Serdaroglu *et al.* [31] introduced a strategy that depends upon wavelet transformation before the analysis of autonomous features to handle default detection of textile fabric images, and Deotale and Sarode [33] proposed an algorithm in light of GLCM and Gabor wavelet extraction and refuse derived fuel (RDF) characterization technic, which describes the structure of fabric and featured the defect position.

Model-based techniques are utilized to tackle the deformity identification issue by expecting that the surface complies with a specific dissemination model and that the model's boundaries are assessed. Yapi *et al.* [35] separated the picture into rudimentary monotonous units and recreated the conveyance of excess contourlet change (RCT) coefficients utilizing a limited combination of a summed up Gaussian model. These strategies can manage different kinds of material textures.

Learning-based methodologies are likewise famous in identifying defaults, utilizing labeling tests to prepare classifiers that recognize default and non-default examples. CNN has strong performance in detecting, segmenting, analyzing, and reporting information, and has been used in a variety of applications in the field of environmental information. From the beginning of the 2000s, with the quick progress of big data and artificial intelligence, convolutional networks have very successfully implemented in data detecting, segmenting [18], [32], and identification of targets and areas in an image [4], especially in tasks involving a high volume of labelled data, such as surface finish [36], industry [10], heath images [37]–[39], and weed detection [16], [40], [41]. In our previous work [2], three famous pre-trained CNN models are compared to detect defect in fabric texture, and the three models automatically detected imperfections on designed texture with an exactness of 96%.

3. MATERIALS AND METHODS
3.1. Object detection

Object-based detection is able to identify single targets in the picture and position bounding boxes around the target. Successful detection of objects requires a system that can handle either the presence (or not) of items in arbitrary situations, can be scaled-independent, view of the item is not depending on the orientation, and can also detect semi-black-out objects. The images of the real environment sometimes include a couple of objects or a huge variety of objects; this may affect the precision and efficiency of the object detector.

Transfer learning is currently deployed in deep learning applications to speed up training and increase the accuracy of the learning system. It means learning different techniques for a pre-trained network and uses it as a starting point. This can be very quick and easy instead of building a new network. You can quickly transfer the learned functions to a new task using a reduced number of training images. The use of pre-trained models accelerates the training and decreases the related fees for collecting massive data sets, labeling, and training models from zero. Training through transfer learning with pre-trained models are suitable for artificial intelligence (AI) applications in industrial inspection, health care, e-learning, and many other areas. Following is a description of the CNN model "DetectNet" employed in this research.

3.2. DetectNet architecture

DetectNet is an item location design made by NVIDIA. It tends to be run from NVIDIA's deep learning graphical UI, DIGITS, which permits to arrangement and begin preparing characterization, object recognition, division, and different sorts of quick models. The DetectNet includes two prototype files delivered by NVIDIA: original single classes file and dual class file. The DetectNet architecture, see in Figures 1 and 2 is composed of five sections according to the Caffe model description folder [42]: i) a data layers embed the he pictures and names and a transformer layer is applying the online data augmentation, ii) a fully connected network (FCN) is used to extract features and predict object classes and boxes delimiters en grid square, iii) loss functions simultaneously measure the error in the two tasks of predicting the object coverage and object bounding box corners per grid square, iv) a clustering function produces the final set of predicted bounding boxes during validation, and v) a simplified version of the mean average precision (mAP) metric is computed to measure model performance against the validation dataset.

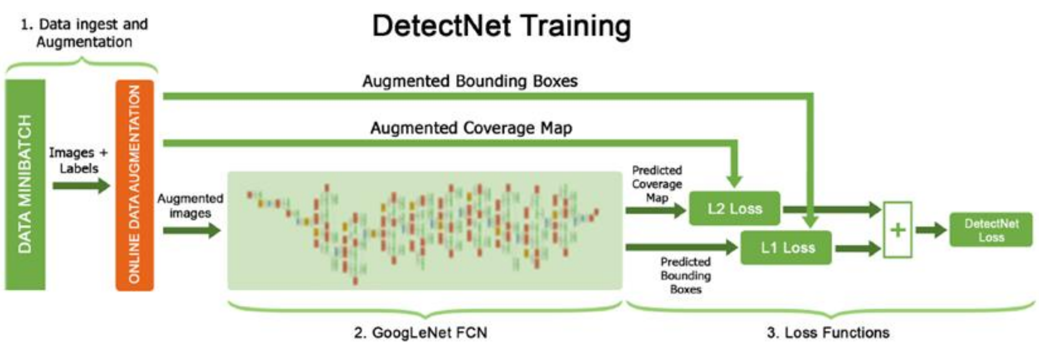

Figure 1. DetectNet training architecture [43]

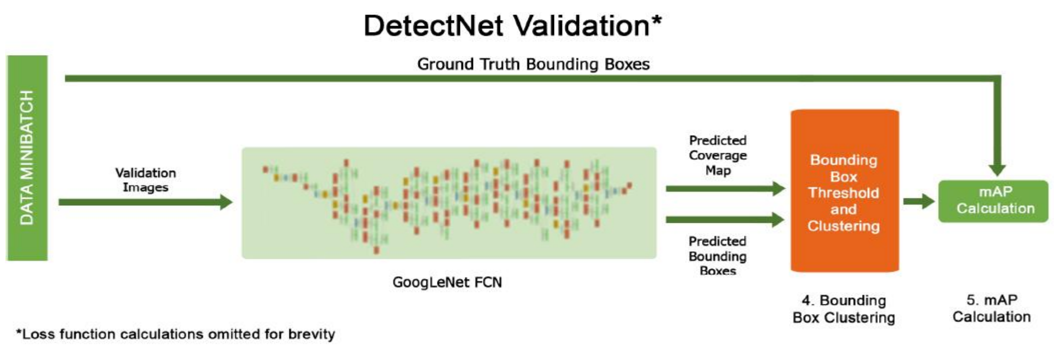

Figure 2. DetectNet validation architecture [43]

DetectNet is a continuation of a famous architecture, GoogLeNet; the DetectNet FCN has similar construction to GoogLeNet except for the input data layer, the final pooling layer, and the output layers [44]. The main advantage of the use of a pre-formed GoogLeNet model to initialize DetectNet is to minimize the time needed for training and to ensure better accuracy for the model. The images in the training set should not be of different sizes. Otherwise, pad them or resize them to equal size, the size must divide the stride. 1,248 by 384 pixels, the default image size of DetectNet, it is divided by 16. DetectNet has the ability to identify boxes that are within the size range of 50×50 pixels to 400×400 pixels, but it is difficult to detect boundary boxes outside this band. Training processes for object detection were realized through the CNN DetectNet conducted with the library NVIDIA DIGITS [45] release 5.0 on the Caffe framework.

3.3. Data preparation

Experiments have been conducted on the popular TILDA database, is a textile texture database which was created inside the structure of the functioning gathering texture analysis of the Deutsche Forschungsgemeinschafts (DFGs) significant examination program "Programmed Visual Inspection of Technical Objects". This functioning gathering created and dissected strategies which made it conceivable to perceive and recognize surfaces of changing sorts [46]. This database consists of eight representative textile kinds, seven error classes and a non-defect class, which four main groups (C1-C4) with each group consisting of two different subgroups, see Figure 3. Therefore, each sub-folder holds just a single fabric kind of image, each of them being divided into 8 sub-folders containing 50 texture images in total. The first sub-folder labeled "e0" includes non-defect images, while the rest of the sub-folders ("e1"-"e7") include defect images.

All images are resized to meet the architecture input size. In the studied cases, NVIDIA’s DetectNet will be used as the main object detection model in DIGITS v5 [47]. IrfanView Software is used to resize images to be of equal dimensions width 1024 and height 512. Labeling images for object detection is a process where we create files that contain descriptions about regions of interest on images (ROI), as shown in Figure 4. ROI consists of a quadratic box or box delimited by a zone in a picture that contains the object to be detected. There are a few formats for labeling object detection data, but NVIDIA’s DetectNet uses the KITTI format. Fiji software with the ALP's plugin was used to label all images, showing the position of the defect in the picture. The defective areas were tagged by defining rectangular ROIs of varying size to surround the defaults as shown in Figure 5. The upper left (x1, y1) and lower right (x2, y2) corner coordinates of the ROIs were identified and translated into text, see Figure 4. Then, the areas were allocated to two categories based on defect availability or not, category 0 for areas with defaults and category 1 for areas with no defects.

Images and labels should be split into 3 folders: training, validation and testing. Each of them should also contain two folders, “images” and “labels”. Validation (Val) folder should contain about 10% of the images and labels from your original folder, testing (Test) folder should contain 10% and training (Train) folder should contain the other 80%. By doing this we are giving DIGITS a folder to be trained on, a folder to be validated on and a folder to be tested on as shown in Figure 6. After every training set using the images and labels in the "Train" file, DIGITS tries to validate the model through the images and labels in the "Val" file. The aim is to achieve the most accurate results possible. Finally, the last step is to test the model using the test folder. The "Testing" dataset was created in order to evaluate the model efficiency on an entirely fresh dataset.

A small dataset of 1,000 images were only used, which was distributed arbitrarily to training, validation, and testing datasets. 800 of the images were used for training, 100 for validation and 100 for testing. The validation and training dataset consisted of 50% non-defective (Class 0) and 50% defective (Class 1). To improve the learning capacity when dealing with small data sets, data augmentation is used to increase the size of data sets by modifying and adapting image focus, luminosity, and sharpness through image treatment technology (IrfanView version 4.54). As a result, the training dataset were increased to 12,000 patches. Two learning models were performed using the same datasets for training (training and validation) and testing, DetectNet has been trained over 300 epochs.

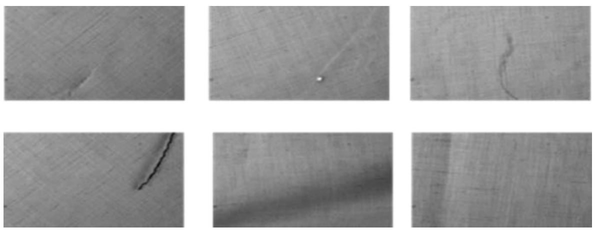

Figure 3. Examples of defective fabric images from TILDA database

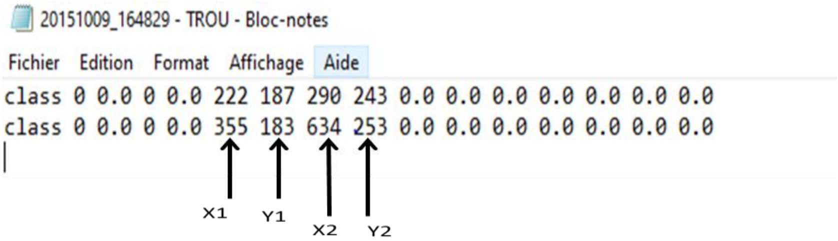

Figure 4. Corner coordinates: upper left (x1, y1) and lower right (x2, y2)

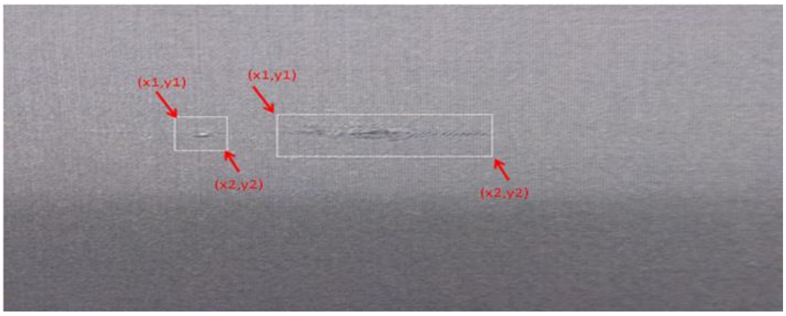

Figure 5. A fabric image showing ROI (region of interest) designated by the blank box, with the corners coordinates

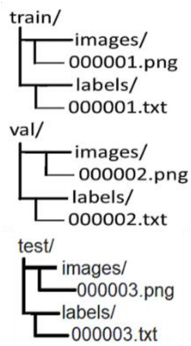

Figure 6. Input folder structure for images and labels

4. RESULTS AND DISCUSSION

The DIGITS implementation survey depends on multiple measures. Nevertheless, in this paper, just four metrics are considered: accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC). The measures are best represented as follow [22]–[24]:

- Accuracy: This is the degree of prediction efficiency; it measures the number of correct predictions.
- Sensitivity: This is the number of correct positive decisions divided by the number of true positives.
- Specificity: The number of true negative decisions divided by the number of actually negative cases.
- The false positive fraction (FPF) = 1-specificity.
- AUC: Is the area under the receiver operating characteristic curve, as shown in Figure 7.
- ROC: Receiver operating characteristic curves, which are defined as a plot of F (1-specificity, sensitivity).

After training the model for NVIDIA dataset in KITTI format, the performance of the model is as shown in Table 1. A significant difference were found in the Area under the receiver operating characteristic curve AUCs between the first and the second models. The sensitivity for detection of the default (class 0) was 0.90 for the first model and 0.92 for the second model. The sensitivity is higher than 0.90 which indicates in 90% of the images the learning machine can properly detect the existence of default. The investigation concluded that the use of DIGITS and DetectNet has achieved higher sensitivity and classification values in textile default detection.

The second model has arrived at 96% accuracy as shown in Table 1, which means that the model achieves high precision. Moreover, the sensitivity reaches 94% means that the model is efficient in identifying the relevant data as shown in Figure 7. Therefore, these experiments have demonstrated good achievement in training the CNN model to detect defect in textile.

Deep learning conquered various different fields namely: health [38], [48], textile [2], [5], weed detection [16], [49] and many others [50], [51]. But not many studies have outlined the implementation of deep learning in textile quality control. The essence of the object detection system is to identify the location of an object in a specific image and to classify them. The database that is used consists of a restricted database of fabric images, to improve the model more fabric images are needed for training the model that will lead to improving it. Currently, hard working in collaboration with multiple textile firms is being done to create a large dataset of more than 100,000 labeled fabric images to boost the performance of the recognition system in data acquisition.

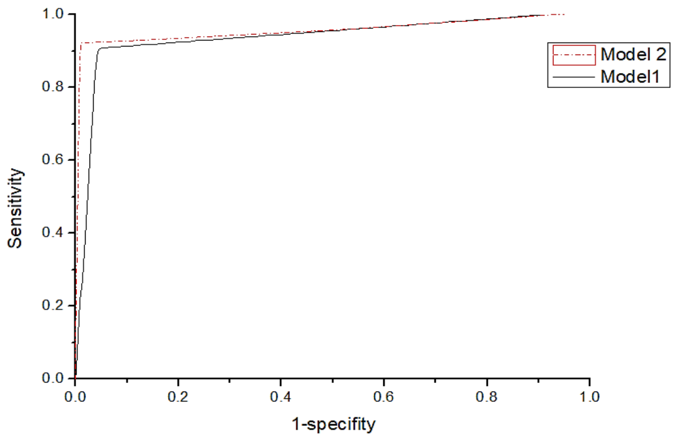

Figure 7. The ROC curves for the first and second models

Table 1. Performances of the deep learning systems "DetectNet" for detecting fabric defects

Variable	First Model	Second Model
Accuracy	0.93	0.96
Sensitivity	0.91	0.94
Specificity	0.96	1.00
AUC	0.93	0.96

5. CONCLUSION

In this paper, a pre-trained convolution neural network “DetectNet” has been fine-tuned to detect the presence of defect in fabric images. The objective of this work was to elaborate an automatic fabric inspection system able to detect fabric defect images. Experimental results show an accuracy of 96% for the second model. The achieved systems were successful in this research. The neural network systems, for the identification and classification of fabric defects, have shown an overall precision equal to or greater than 90%. In addition, a system containing these models for identifying and classifying a single failure provides an automated mechanism that highlights and displays the probability of classifying multiple types of failures with the accuracy shown in the previous paragraph. However, despite the promising results, there are still possibilities for improvement which are proposed as a future work, recognizing fabric defect in images with a multi-label approach is the essential aim of the convey.

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