Journal of Artificial Intelligence and Capsule Networks (ISSN: 2582-2012)
www.irojournals.com/aicn/

Leather Defect Segmentation Using Semantic Segmentation Algorithms

Aashish Ghimire[1], Aman Mahaseth[2], Ramesh Thapa[3], Suraj Ale Magar[4], Sushil Kumar Singh[5], Salik Ram Khanal[6]

[1-5]Department of Electronics and Computer Engineering, Paschimanchal Campus, Tribhuvan University, Pokhara, Nepal
[6]Center for Precision and Automated Agricultural Systems, Washington State University, United States

E-mail: [1]aashishghimire9999@gmail.com, [2]mahaseth.aman123@gmail.com, [3]rthapa@wrc.edu.np, [4]surajido111@gmail.com, [5]iamsingh889@gmail.com, [6]salikkha@gmail.com

Abstract

Leather is one of the essential materials in our life. It can be used widely to make different industrial products. Products made from leather are strong, expensive and durable which lasts for decades. So, It is very important for the industry to make a defect free product for their maximum profit and good customer feedback. Quality inspection is one of the important processes in the textile industry. It is done manually in most of the industry which is time taking, expensive, less accurate and requires lots of people. The main aim of our research work is to replace the manual process with automatic leather defect detection techniques which can save both time and money and increase the rate of production in the company. In this article, we proposed a deep learning-based semantic segmentation model that detects defects in leather images and highlights the defect with proper defect type. The experiments were carried out using the MVTEC leather dataset. The input images are changed into 256*256 pixels and then converted to gray-scale image and finally a semantic segmentation algorithm is applied to detect the leather defects. The experimental results are evaluated and compared using various semantic segmentation algorithms. We obtained the satisfactory result with evaluation metrics of 72.1% Intersection of Union (IOU) with 82.59% F1 Score on one of the semantic segmentation architectures Mobilenet_unet.

Keywords: Semantic segmentation, gray-scale image, intersection of union, textile industry

1. Introduction

Leather defects means imperfections in the surface or structure in the leather products resulting in the bad appearance or decreasing the durability of the products. Some of the

DOI: https://doi.org/10.36548/jaicn.2022.2.005
Received: 26.05.2022, received in revised form: 25.06.2022, accepted: 09.07.2022, published: 20.07.2022

common defects in leather products are Color, Cut, Fold, Glue, Poke and so on. In most of the industry, the process of detecting defects in the product is tedious and time taking.They try to do it manually and the cost of process is high as it requires a lot of people for quality inspection of the product [1]. Defect detection plays an essential role in quality control in various textile products [2]. It is very important for an industry to replace manual processes with advanced technology such as artificial intelligence, computer vision with hardware implementation which can save time, money as well as detect defects in leather with more accuracy than manual process.

Defect detection in leather images can be done by either classification or object detection or semantic segmentation. Various computer vision techniques and technologies have been implemented in different ways by different people for the detection of defects in leather.Some proposed algorithms are not fit for detecting all types of defects in leather images and give less accuracy on different defect types and different dataset. Some proposed methods are highly expensive and take more time. So,they are still unable to replace the manual process of quality inspection in the textile industry completely. People are still heavily engaged in the textile industry for quality inspection of leather products especially in underdeveloped and developing countries.These are the factors which give us extra motivation to do this work.

We proposed a semantic segmentation model using Mobilenet_unet, Resnet50_unet, Mobilenet_segnet, Resnet50_segnet and compared the performances of all algorithms which can detect the defects in the images as well as classify the types of defects in the leather images.The proposed model takes the image as input and gives a segmented image as output. Satisfactory results have been obtained on major different types of defects using our model.

2. Related Work

With the introduction to deep learning, various research studies have been carried out to detect the defect in leather images. Jun et al. [3] proposed a two stage-strategy of semantic segmentation which consist of fixed-size square slider and histogram equalization. Fixed-size square slider was used for cropping the image and then histogram equalization was used for the image. Presence of defects was first predicted using the Inception-V1 model and then defect types were predicted using the LeNet-5 model.They compared the results of different models such as AlexNet, Vgg-16, Inception-V1, Inception-V2, Inception-V3 and Resnet_50. Among them, Inception-V1 gave the best prediction with an accuracy of 91%.

Anagnostopoulos et al. [4] proposed a computer vision approach for textile quality control. Here, the algorithmic process based on simple statistical measurements, thresholding and morphological operations was proposed. The whole inspection system was made up of inspection bridge, defect analysis computer system, quality control console and the archive system of defect databases. The main algorithm consists of 3 parts: First, Normalization of image with correction of non-uniform illumination, second image processing procedure which detects irregularities in the normalized image and revealed possible flaws in textile and the third part was identification of Region of Interest (ROI) within the image. In this way the experimental result was obtained by using the total sample of 50 images consisting 5 images for each 10 kinds of flaws with the accuracy of 84%. This proposed system concluded that the applied algorithms can offer increased accuracy on great diversity of textile types.

Tong et al. [5] proposed a Nonlocal Sparse Representation Approach for the defect detection in the fabric images. A model consists of three different operations. Image Preprocessing, image restoration and thresholding operation was developed for the detection of defects in fabric images. Sparse Representation helped to estimate the region of non-defective regions of the Input image which helped to separate the region of defective and non-defective regions and got an accuracy of 94.6% on TILDA dataset and 94.1% on their own dataset.Jeyaraj et al. [6] proposed an advanced deep learning technique. The research focused on building computer system defect detection in the textile industry. Classification model was developed based on the ResNet-512 based CNN and got an accuracy of around 96.5% and 98.5% precision. One of the main achievements of research was they got better results on the patterned fabric images. Li et al. [7] proposed a Bag of tricks based on Cascade R-CNN which was used to improve the precision for detecting defects. Three tricks were proposed. Multiscale training was used which scaled the image into images of different resolution and would adapt in the different scale's distribution. Secondly, A dimension cluster method was used for balancing the dataset of the defect images. Also,Soft non-maximum suppression was used for avoiding the overlapping of the same category of the defects. By using these tricks, the fabric defect detection was increased by 8.9% on the CNN detection algorithm. Peres et al. [8] proposed Generative Adversarial Networks for Data Augmentation in Structural Adhesive Inspection. The generation of real dataset and its characterization were discussed and then the generation of synthetic adhesive images was done by using StyleGAN2-ADA. On execution phase, training and validation steps were performed using the YOLOv4Tiny object detection model. A total of 594 images were generated from 143 real images and four different models were trained on four different datasets: synthetic, real, augmented (simulation by previous research) and augmented (GAN from this research). Among them, models trained on augmented (GAN) provide high precision on testing phase.

3. Material and Methods

3.1 Datasets

The dataset we used was the MVTEC leather anomaly dataset obtained from MVTEC official website[9], [10]. The dataset contains original images and ground truth images of leather which includes five different types of defects: Color, Cut, Fold, Glue, Poke.

3.2 Proposed Method

Neural networks are the backbone of most of the artificial intelligence algorithms. The neural networks help to process data and enable the computer to take the decision in the same way as the human mind does.The neural network consists of input, hidden and output nodes which are interconnected by weighted edges.

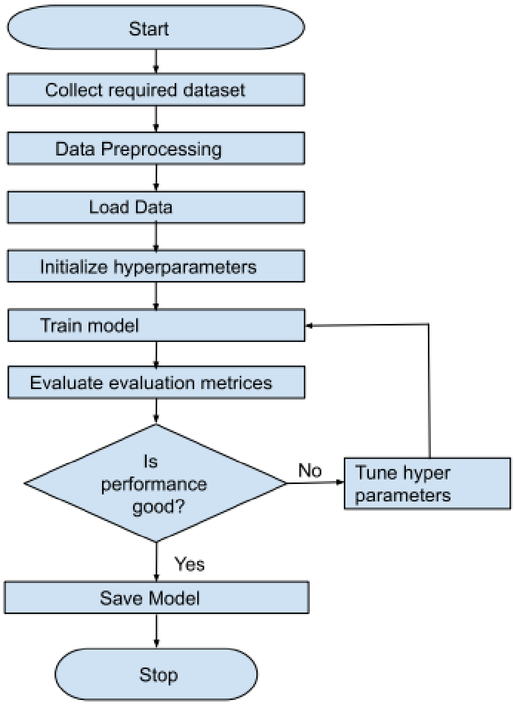

Figure 1. Flowchart of model building using semantic segmentation models

In this article we used the semantic segmentation model as the segmentation to implement defect segmentation which are also the deep artificial neural networks used to analyze visual images, classify them, cluster them and recognize objects within them. The steps followed in model building for our research is shown in Figure 1 which is followed for each CNN architecture so that model can be saved and performances can be compared later.

3.3 Experiments

The main goal of image segmentation is to represent an image into something that is more meaningful and easier to analyze. For that purpose, we examined the performance of various convolutional neural network models. Here we used several encoders-decoder based semantic segmentation architecture to make a fully connected convolutional neural network and compare the results obtained from them.We used mobilenet[11] and resnet50[12] for feature map extraction,and using them architectures like Unet[13] and Segnet[14] are implemented.All of these four architectures were provided with our processed dataset and training was done accordingly. We have experimented with all four architectures and compared the performance under different parameters namely Intersection of Union, F1 Score,Recall. Precision and Loss with keeping batch size as 8 and adam optimizer in 50 epochs.

4. Result and Discussion

The dataset is obtained from MVTEC official websites.The dataset includes original defect images and mask images with different defect types such as Color, Cut, Fold, Glue, Poke defects. The experiments were carried out using four different convolutional neural networks using Mobilenet,Resnet as encoder and Unet and Segnet as decoder. The input images were changed into 256*256 pixels and then converted to gray-scale image and finally Convolutional Neural Network algorithm was applied to detect the defects. Python built-in libraries such as Keras, Tensorflow, Tkinter, Numpy, Pandas were used in the project.Adam was used as an optimizer and batch size of 8. Categorical Entropy was used as a loss function and the model was trained with 50 epochs. The Intersection of Union, F1 Score, Precision, Recall and Loss were used as an evaluation metrics and results are illustrated in the Table1. We have obtained the best result in Mobilenet-Unet with mean IoU of 0.7210 and mean F1 score of 0.8259. The experiment results with original image, original mask image and output from different models are illustrated in Fig below. Images were divided into train and test images. Test images were used for the testing of the model.We have got good results as defect regions were easily detected with different color representation for different types of defect by which we can classify defects.

Table 1. Evaluation metrics for four semantic segmentation models trained on Dataset

Model	Mean IoU	Mean F1 Score	Mean Recall	Mean Precision	Loss
Mobilenet_unet	0.7210	0.8259	0.8103	0.8648	0.0090
Mobilenet_segnet	0.6604	0.7790	0.7303	0.86055	0.0141
Resnet50_unet	0.706	0.8123	0.7709	0.8876	0.0676
Renet50_segnet	0.6829	0.7910	0.7646	0.8547	0.018

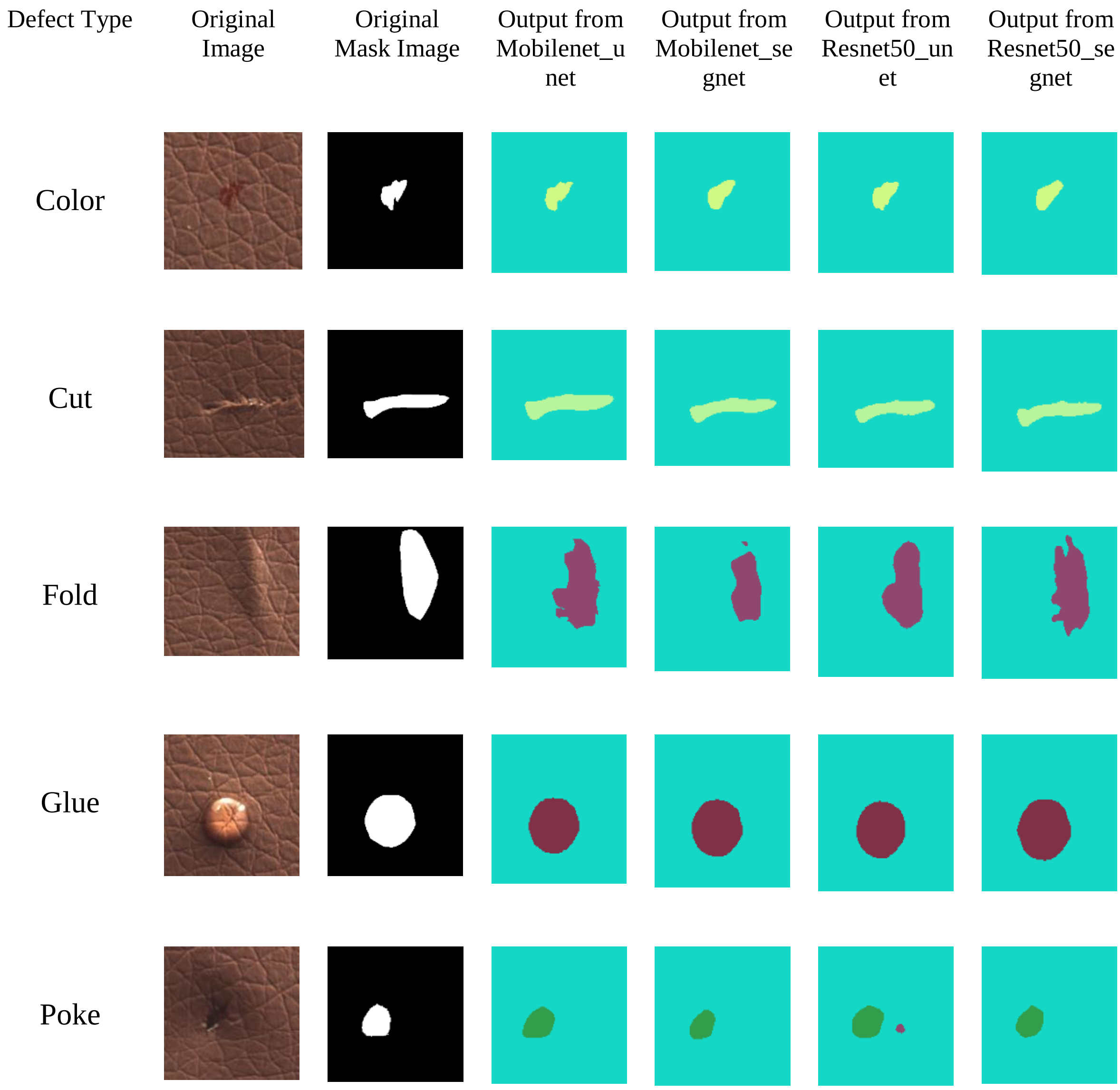

Figure 2. Experimental results on different models

One major limitation of our proposed work was lack of sufficient data and diverse pattern of data. We have only used 546 images of similar type for this work. We can still increase the accuracy, improve the results by collecting more data and different data types in the future.Taking the project to the outside world, where all developers from around the world can contribute, will assist to considerably improve the model, as the combined work of all the smart brains on the planet will be put to use. Making the project open-source on GitHub, so that developers can contribute, raise issues, fork it, and improve the coding.

5. Conclusion

In today's world automated defect detection is the hottest topic in the manufacturing industry. In this research project, we have implemented the basics of Computer Vision and Deep Learning to detect the defects in the leather images. We have tried different semantic segmentation algorithms and trained the leather images with different hyperparameter values and got the one with the best evaluation metrics. We too tried different optimization algorithms to improve the performance of the model. We have obtained the best result in Mobilenet_unet model with mean IoU of 0.7210 and mean F1 score of 0.8259. We can still improve the performance of the model by increasing the number of images in the future. As the result is satisfactory, the proposed model can be implemented in the textile industry.

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