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

Samah Noaman Sahi SAHI

Master`s Thesis

Supervisor

Asst. Prof. Dr. Timur İNAN

İstanbul, 2023

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The thesis titled BROKEN STITCH DETECTION METHOD FOR SEWING OPERATION USING CNN FEATURE MAP AND IMAGE-PROCESSING TECHNIQUES Prepared by SAMAH NOAMAN SAHI SAHI and submitted on 22/12/2023 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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Samah Noaman Sahi SAHI

Signature

DEDICATION

I dedicate the work for my supervisor, who has been instrumental in helping me through the whole thesis process, and also to my parents, who has always been there for me during difficult times.

ABSTRACT

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

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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 have received much 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 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, Algorithm.

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ABBREVIATIONS

CNN	:	Convolutional Neural Network
DL	:	Deep Learning
ML	:	Machine Learning
WT	:	Wavelet Transform
GLCM	:	Gray-Level Co-occurrence Matrices

1. INTRODUCTION

1.1 BACKGROUND

Quality in industrial processes has become increasingly important and cost reduction and process optimization are becoming increasingly necessary [1] 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 have received much attention regarding defects is the weaving process. According to [2] the success of weaving is significantly linked to its success in reducing 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 [3-5] Two factors are important in weaving a piece of fabric. Firstly, the speed of the loom 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 by about 45% to 65% of the sale value. There are first and second-quality fabrics according to [4] There are always going to be obvious flaws on the surface of the fabric when it comes out of the process of making textiles. These defects come in a variety of sizes and shapes and are caused by things such as machine failure, damage, and pollution, all of which make it more difficult to sell completed products at a price that is satisfactory [1].Manual detection of non-conforming products is possible, but it has a low accuracy of 60–75% [1] due to employees' lack of concentration and poor visual judgment. Thankfully, over the past few decades, clever algorithms and methods that can automatically identify fabrics with very excellent outcomes [2, 3] have been developed. The current state of the art in automatic defect detection technology for fabrics presents a persistent challenge in the pursuit of efficiency in today's textile industry. This challenge is presented by the fact that the textile industry continues to develop new technologies.

Based on the strategy for extracting features, the method for automatically finding flaws can be broken down into two different approaches, or strategies. These approaches are the traditional method and the deep learning method. Methods that have been around for a long time generally rely on artificially designed features with the intention of representing texture flaws. In particular, it is possible to subdivide it into four different subcategories [4], which are referred to as spectral, statistical, structural, and model-based techniques, respectively. When applied to certain categories of products, these traditional methods are capable of producing satisfactory results; however, modern production requires the management of complex and varied image texture patterns, along with the assistance of appropriate hardware equipment and a production environment. Generally speaking, it is relatively difficult to generalize conventional methods in new operating environments and to incorporate them into new designs in most cases. This is also true in most cases. In recent years, a great number of networks for the identification of defects have been developed in order to take advantage of the qualities of deep neural networks.

The former is defect-free, while the latter may contain some defects in their texture or surface. As it is a product that goes through delicate processes, such as weaving, it is very difficult to obtain top-quality products. Thus, a large part of inspection and quality verification concerns the reduction of the occurrence of defects in fabrics in the initial stages of manufacture In fabric manufacturing, inspection is done first to locate a defect and later to correct the problem that leads to that defect This process leads to a decrease in second quality products. These, in turn, have a lower market value since they have problems in their manufacture, from flaws in the weft to even stains, for example. This process for a person can become extremely tiring since the human visual processing capacity has its limitations and weaknesses. Inspection performed by people has become obsolete in defect detection. One of the factors that led to this finding is productivity. a person can only inspect a roll of fabric at 20 m/min.

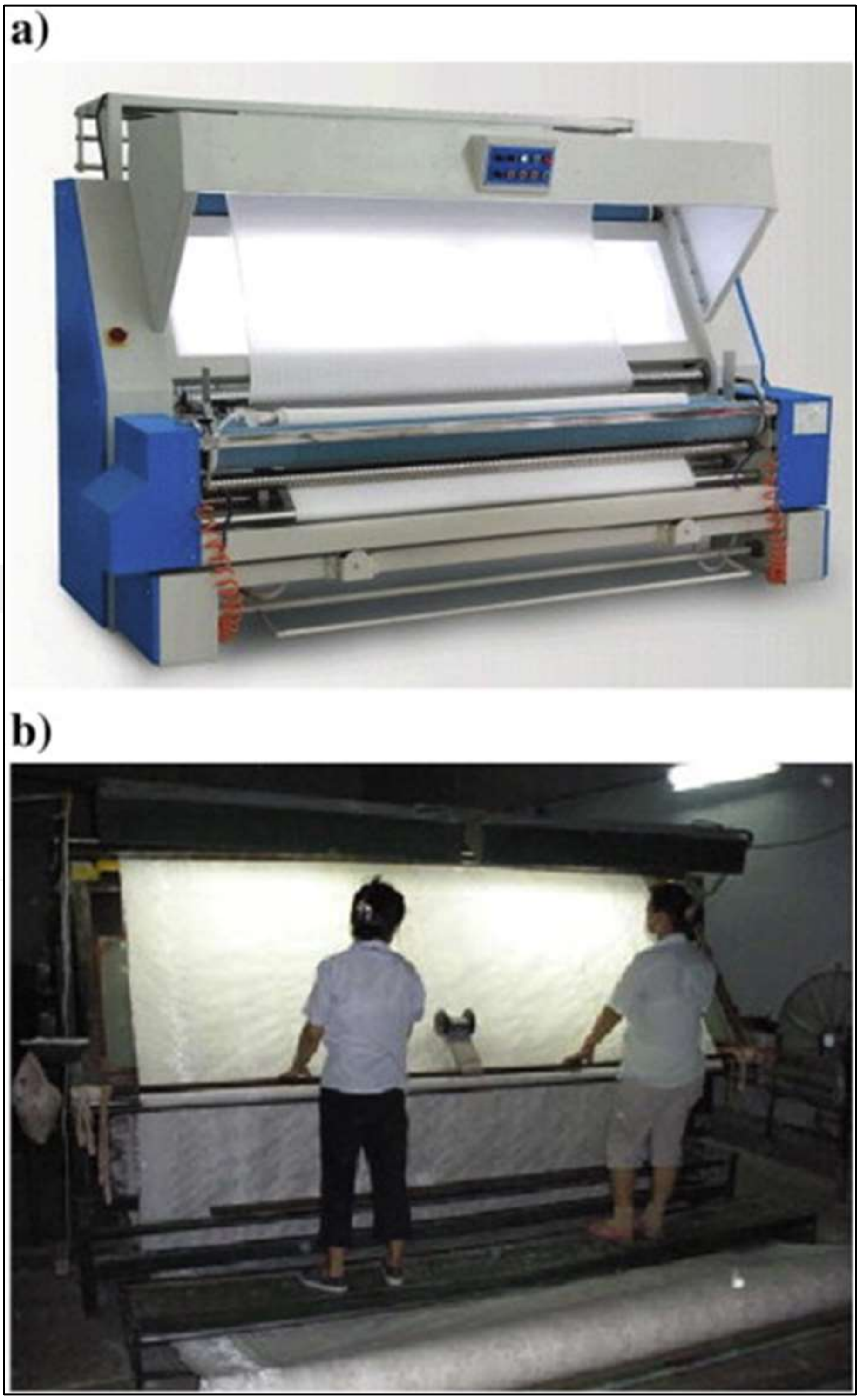


Figure 1.1: Fabric Defect Detection Machine.

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 1.1 shows better how the inspection is carried out by a specialist in the production of a factory.

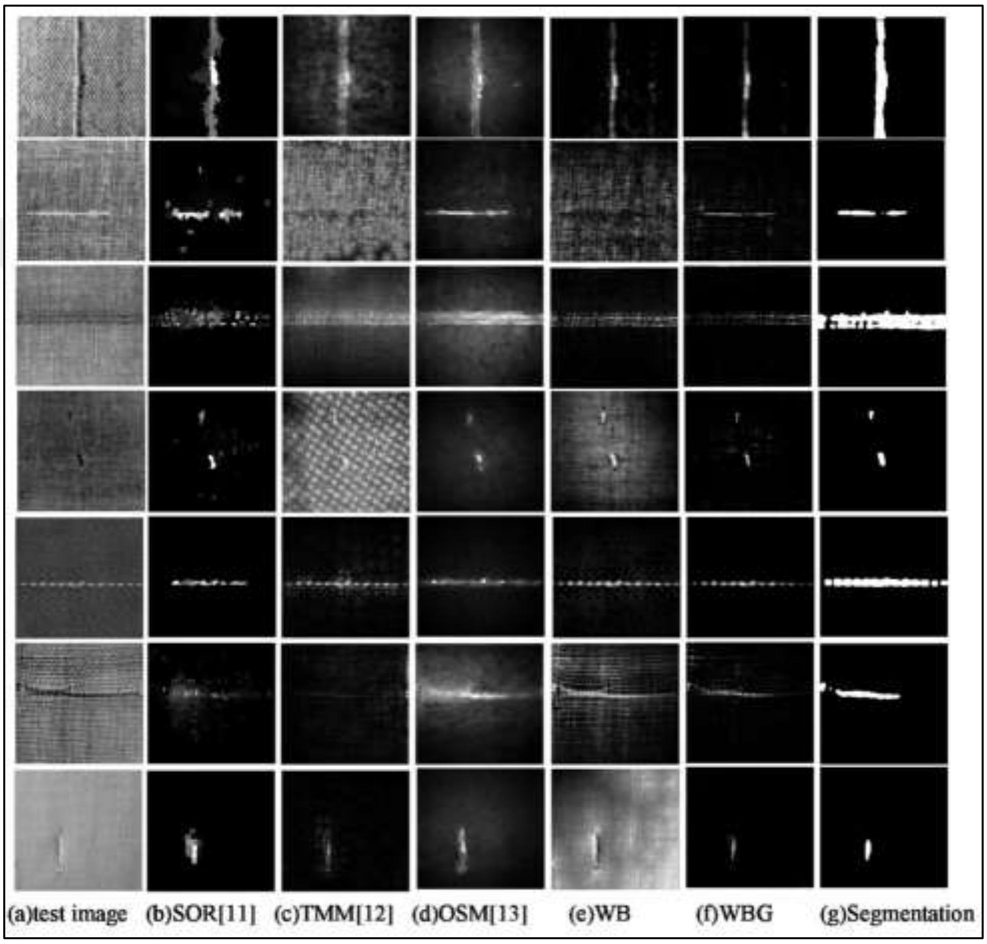


Figure 1.2: Example of Fabric Defects [3].

As soon as the specialist finds a defect, he stops the machine, records the defect and its location, and restarts the engine. The registration is often on the fabric itself, made with a chalk mark at the location of the fault. For each roll of fabric inspected, the number of defects per meter is calculated by the previous defect rates, that is, the rolls that have already been inspected, are left with the machine operator Once the operator notices a very high rate of defects, the notice is made to the production department. Thus, due repairs can be made to reduce the number of mistakes made. In defect recognition systems like the ones described above, it is practically impossible to reduce the error to zero. When the production speed was slow compared to the current one, this inspection system worked well. The evolution of techniques and especially of weaving machines made this a difficult task to manage. There are countless problems related to human visual detection Among the main problems related to detection by people, the following can be cited: People who are specialists in this task are difficult to find; People are slower than machines; Inspector tire quickly, as this is an expensive task; There are many types of defects; When a fabric 1.4-2 meters wide at a rate of 20 meters per minute is unrolled, the inspector's accuracy is 50% on average and at most 80%. Tissue inspection is an extremely important task in today's industry. For the reasons mentioned above, developing a computer vision system for this process is of great importance. Obtaining a reliable quality system guarantees product reliability and, consequently, better results. An automated defect detection system improves product quality and productivity production speed of the weaving machines increased a lot over time. The increase in speed takes the demand to recognize and correct faults to more difficult levels. It is therefore necessary to differentiate two types of inspection. Online inspection and offline inspection, the former is still called real-time inspection online systems provide data on current production and are still located on the production line itself so that measurements can be taken at the same time. On the other hand, offline systems are located at the end of the production line, causing a loss of fabric quality, since failures are only computed at the end of the process. The study of computer vision systems has been increasingly relevant from an industrial and academic point of view. To imitate the great variety of human functions, technology was the great driver that made humanity advance from manual to mechanical and then from mechanical to automatic the advancement of image processing techniques and also machine learning algorithms are making industrial processes more and more intelligent. The combination of these two practices made possible numerous applications in industry, agriculture, medicine, and others. It is natural to seek to create machines that can recognize patterns The ability of human beings to learn is and was fundamental to evolution. Computer vision systems try to mimic, in a way, this ability to learn and recognize patterns. 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 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.

1.2 OBJECTIVES

1.2.1 General Objective

The objective of this work is to develop a system capable of classifying different types of tissue defects through image processing techniques.

1.2.2 Specific Objectives

a. Use Wavelets to extract information from tissues.

b. Use supervised machine learning techniques to make defect classification possible.

c. Classify fabrics into different types of defects.

d. Use the CNN algorithm to improve the classifier response.

e. Get the system validated with cross-validation.

1.3 PROBLEM STATEMENT

The automation of processes has become fundamental for increasing productivity and, consequently, competitiveness in the industry. As previously mentioned, human beings have been gradually mechanizing and automating processes since the industrial revolution. Jobs that are repetitive and do not involve any kind of creativity started to be developed by machines. As the detection of defects is a repetitive and exhausting process for a person, an intelligent system is necessary. The textile industry in the 90s represented 14% of all jobs in the industry fact demonstrates how important this market was for Turkey. With the opening of the market also in the 1990s, through public policies in Turkey, these heavy investments were necessary since the products coming from outside the national territory had specialized products. An important fact is that the number of jobs has decreased with what was previously the modernization of the industrial park. All this investment and modernization brought more quality to the material produced, reduced costs with employees, and speed in production. These factors are addressed in this work and show how industrial modernization is and was important for the world market. Turkey also needs to produce machines capable of producing better, quality and competitiveness, to obtain technological autonomy, according to the innovation law. Today, according to 2015 data from (the Turkish Association of Textile and Clothing Industry), Turkey ranks as the fifth largest textile producer in the world. Thus, the development of a fabric flaw detection system can help Turkey to stand out even more in the textile market, even though it is already one of the largest players today.

1.4 HYPOTHESIS

The use of a computer vision system can improve the fabric defect detection system in the industry. 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.

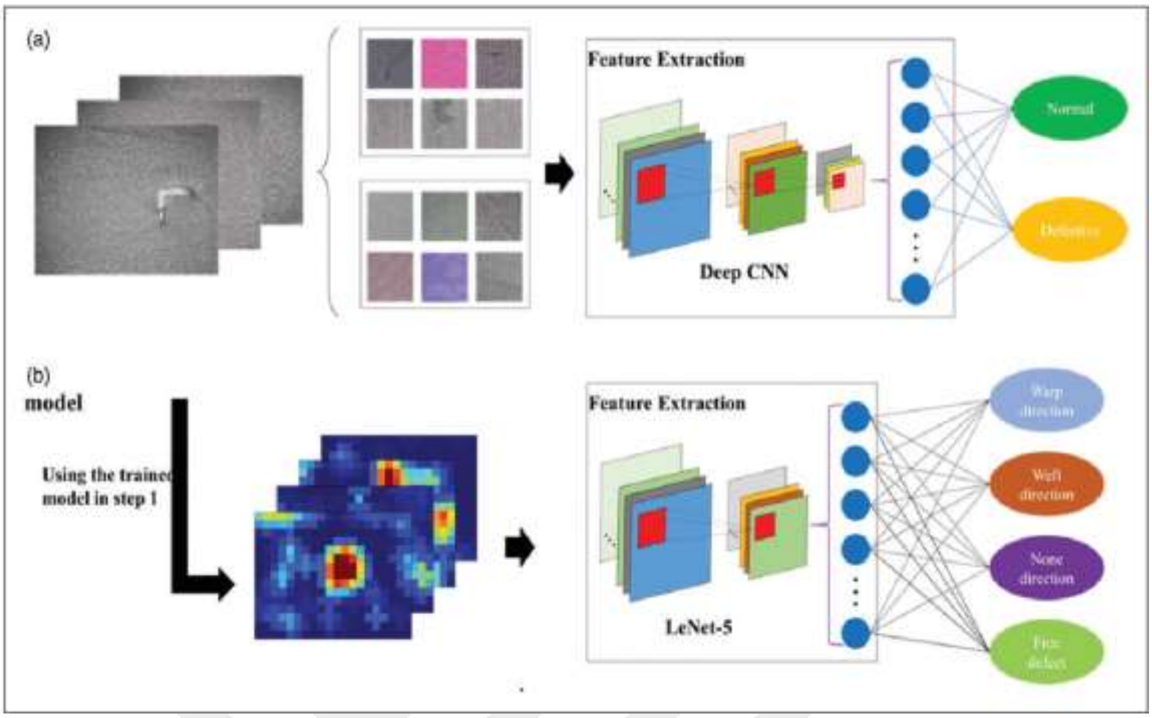


Figure 1.3: Diagram of The Proposed System.

1.5 METHODOLOGY

a. Survey the state of the art in methods of recognizing defects in fabrics.

b. Create the database, as well as the set of images to be used.

c. Extract information from the image with the Wavelet Transform.

d. Test different classification algorithms to find the best answer for this problem.

e. Improve the performance of the classifier algorithms through the CNN algorithm.

f. Validate the system using the k-fold cross-validation technique.

2. LITERATURE REVIEW

2.1 INTRODUCTION

In this area of research, the two basic kinds of fabric defect detection systems being examined are learning-based and classical methods. Statistical, structural, spectral, and model-based algorithms all rely on feature engineering conducted using previously obtained data to work successfully. Traditional machine learning approaches and deep learning methods both have space for improvement in terms of subdivision. In recent years, mathematical algorithms have been applied extensively in machine learning, resulting in stratified outcomes across a variety of fields and sectors. The achievement of these results was made possible by employing machine learning to examine and evaluate data.

2.2 FABRIC DEFECT DETECTION ALGORITHMS

2.2.1 Statistics Algorithms

[12] 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 [13, 14].

Anandan et al. [15] 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. [16] 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 to apply).

Song et al. [17] compute the membership degree of each segment of the fabric 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.

According to Gharsallah et al. [18], 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 textured 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.

In large-scale industrial production around the globe, modern fabric defect detection is used frequently because the same machinery and procedures can result in repeated patterns on the surface of the product. Notable developments in automatic fabric detection have examined analytical techniques for analyzing periodic patterns because the reference to similar patterns in the algorithm can help find potential anomalies. In particular, Ngan et al. [10] suggested a motif-based defect detection method that included a lattice extraction preprocessing step, which segmented the fabric image into non-overlapping basic units via a computational model. In order to find flaws in a fabric's smooth pattern, Jing et al. [11] used the distance matching function to break up the image into smaller segments, and then slid the CNN model trained on transfer learning across the entire image. The core of these works is to transform the issue of detecting fabric defects into one of estimating lattice similarity, a technique proposed by Jia et al. However, high stationarity and low complexity of the pattern period are typically required for image periodic pattern analysis based on computational techniques. Additionally, a fundamental problem with these works is that lattice segmentation prevents certain sections of the image from effectively communicating with one another.

Consequently, depending on comparison between minor details may ignore the overall image's abnormality.

This article makes a proposal for automatic fabric detection using a semantic segmentation network and a repeated pattern analysis algorithm. The proposal is based on the problems that were discussed earlier. Specifically, the implementation of our method does not pass the comparison between basic patterns but instead obtains repeated pattern information through pre-computation and uses it to guide the network in the high-level semantic space to understand repeated feature knowledge and highlight potential defect areas. The repeated pattern detector [15] uses CNN feature activations to recognize spatial repeating patterns in order to improve its recording of high-level contextual semantics and its extraction of periodic primitives. This helps the detector do a better job of both. Because it feeds the network information about repeated patterns in the shape of picture labels, our strategy necessitates a significant amount of pre-computing. In an effort to cut down on the amount of time spent on pre-processing, we will try to substitute it with semi-supervised network learning. In this semi-supervised method, the initial picture and repeated pattern labels are fed into separate fused semantic segmentation networks that have common parameters. During the iteration of the gradient, the network group is required to segment images of fabrics and emphasize patterns that appear repeatedly. After training, the network is stripped down to its most fundamental nodes, thereby preventing the model from making use of any additional inputs and ensuring that it is conscious of any potential repeated pattern knowledge.

2.2.2 Spectroscopy Methodology

Spectral approaches include transforms such as the Fourier transform, the Gabor transform, the wavelet transforms, and the discrete cosine transforms [22–24]. 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.

Li et al. [32] offer an automated method for recognizing fabric flaws that employ 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.

Rebhi et al. [33] use the 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.

2.2.3 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. Ngan et al. [34] 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.

Jia and Liang [35] 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 subsequent work, Jia et al. [36] introduced a novel approach based on lattice segmentation and lattice templates [37]. 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 [37] allowed for its further enhancement.

Chang's [38] study proposes a novel template-based correction technique for periodic-structured fabric photos. The variation regularity is used to divide a fabric picture into lattices, which are subsequently altered to lessen the degree of misalignment between them. In the first phase of the procedure, the faulty lattices are identified, and then the issue areas are separated. When retouching images of patterned textiles, lattice segmentation, and template-based correction are preferable approaches to explore. The idea by Shi et al.

involves a low-rank decomposition of gradient information coupled to a structured network. According to the data in the structured graph, this image is initially separated between areas that do not contain any flaws and those that do (e fabric image). Adaptive thresholding is used during the merging of the lattices. Using the findings of the preceding segmentation stage, the problematic areas are emphasized by performing a matrix decomposition in the last step. On a normal database, the solution we've shown is preferable to the other accessible alternatives.

According to Abouelela et al. [40], faults in the fabric may be identified using basic statistical features such as the median, the mean, and the standard deviation. According to, time efficiency is a crucial aspect of every production process (the author.) Therefore, the author emphasized the speed of real-time operations above the complexity of calculating the essential properties. e) The technique that has been suggested makes it easier to spot faults that display a significant amount of dimensional fluctuation.

2.2.4 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 [41], more energy is acquired to discriminate between regions with defects and regions without flaws. To reduce the frequency of false positives and false negatives, a Gaussian mixture model is used to represent the energy variance [42]. 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 [43].

Shu et al. [44] devised a technique based on principal component analysis and nonlocal average filtering to improve the fabric texture and minimize the 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 can 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.

The SVDD model proposed by Bu et al. [45, 46] serves as the basis for the technique proposed by these authors. Numerous fractal attributes are employed to train the Gaussian kernel function, and the optimal values for each of these traits are chosen. Numerous datasets demonstrate that this combination is good for identifying individuals (e).

Bu et al. [47] have presented a technique based on the SVDD model that may be used to extract features. This technique combines an autoregressive (AR) spectral estimation model with the Burg algorithm. Campbell et al. [48] advocate utilizing two distinct statistical models for distinct methods in this investigation. If the first procedure is adhered to, picture binarization has a greater probability of occurring. The process of finding defects in repetitive weaving patterns employs a different technique known as the discrete Fourier transformation. Ultimately, a clustering method based on a model is employed to identify problematic sites.

Tsang et al. [49] present a technique for identifying patterned materials that they refer to as the Elo rating (ER). Based on the competitive character of sports, this strategy was developed. When separating fabric pictures, standard-sized dividers are often employed. Using Elo point matrices, it is possible to adjust the estimated matches between divisions. It is fair to anticipate that the (e-fault area) category will win the competition. Using the most sophisticated method available, which includes evaluating a database including dot, star, and box patterns, comparable findings were achieved. These tools were utilized to conduct this analysis.

3. MATERIALS AND METHODS

3.1 INTRODUCTION

The fabric industry is extremely active and produces a diverse variety of goods that are used as raw materials in a number of other industries. The quality of the finished product, which is the fabric, or to be more specific, the fabric weft, is the most important element in determining the outcome of this field. A general rule that applies in an industrial setting is that the value of a fabric weave is determined by the existence of faults and the locations of those faults [42]. The definition of the quality component in this sector takes into account this criterion in its formulation. In the first part of this chapter, we discuss the manufacturing environment in which fabric is produced as well as the difficulties that can arise during its inspection. In the second part of this article, we will discuss conventional examination. In the final part of this article, we will talk about automated inspection. In the fourth part of this article, we will go over the evaluation parameters for texture fault detection algorithms based on the current state of the art.

3.2 FABRIC INDUSTRY

The reel is driven by a motor to prevent it from being cut. A carriage is responsible for pushing one or more needles in one direction to form a knot. The succession of this operation produces a line of knots also called a line of fabric weft. Depending on the nature of the weft produced, the number of heddles and the number of needles may vary. In some other knitting systems, there is an integrated linting system that is responsible for the production of the woven fabric before passing it to the knitting system [50].

Figure 3.1 shows a simplified diagram of an industrial knitting system. This diagram shows only the knitting process and assumes that the material is already produced.

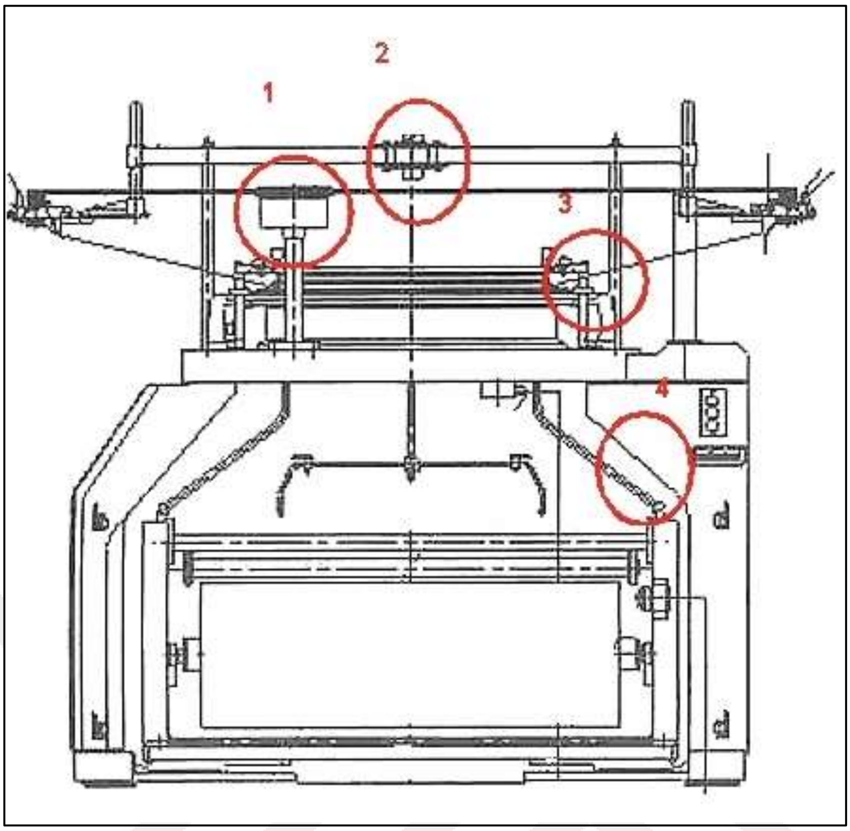


Figure 3.1 Industrial Knitting System.

During the process of knitting a fabric weft, several types of faults can occur. The ballast used can be cut resulting in a gap in the west, a spill of oil can be caused by the knitting material or a color difference can be marked during the dyeing of the fabric. The following are the most common faults in the manufacture of fabric [39].

a. If an l of warp is missing in the fabric for a short or long distance.
b. breakage: If a weft l is missing in the fabric for a short or long width.
c. Floaters: This is a type of doughnut where a warp or weft loop is placed above the surface of the fabric. This is the consequence of the absence of interweaving of two series of webs.
d. Curly weft: If the warp or weft threads are very twisted or stretched.
e. Slugs: When the weft is unclean and contains slugs or irregularities of diameter.
f. Stitching: The ends and spikes are not stitched in the correct order in the structure.
g. Irregular Density: If the selection density that is taken per inch varies due to mechanical failure.

h. Hairy fabric: The fibers in the cloth have been roughened before, during, or after weaving.
i. Holes: The presence of small holes in the fabric.
j. Oil stains: Stains caused by the lubrication of the mechanical parts of the knitting machine.
k. Shedding stitch: Caused by the stopping and shedding of a weaving machine.
l. Extraction: When a fabric row is dyed, the depth of tint of the color may vary from one place to another along the length of the fabric.
m. White stain: If the grey fabric is made of a cotton-polyester blend or other synthetic materials in a negligible amount, after dyeing the brew, the white polyester remains, resulting in white spots in the fabric.
n. Dyeing process: During the dyeing process, bands of color denser than the assumed color may appear.
o. Colored stain: During the dyeing process, colored stains may occur due to improper knots and fibers in the fabric.

The diversity of fabric defects makes the inspection task more difficult. In addition, the question is: when exactly is a d e f e c t considered to be present? Furthermore, a defect may be apparent on a small scale, i.e. when viewed locally, whereas on a large scale, or wider window, the same defect is no longer visible. The best-known example of this kind of problem is the hole (see the 7th condition above). Depending on the size of the hole, this defect can be detected locally but not on a large scale. The opposite case is also a problem; a defect can be remarkable on a large scale while not being noticeable locally. The most common example is that of the frizzled grids (2nd need mentioned above). Looking at the raster on a large scale, we can notice the texture defect and we can notice without a doubt that it is a defect, while looking locally this defect is no longer remarkable.

The problem we are trying to solve is the automatic detection of faults and it is not about classifying the detected faults although this classification is useful. The human being can distinguish the faults in the two scales (large scale and small scale) thanks to its complex vision system.

Our work aims to propose an automatic method to discriminate between damaged and healthy areas in tissue images. This method will be applied by computerized systems and should ensure a better inspection with minimum errors.

3.3 TRADITIONAL INSPECTION OF FABRIC

According to the literature [42], there are two methods of fabric inspection. The first is to inspect the fabric during production. In other words, when the knitting machines are producing the wefts, an inspector (human) is in charge of looking at the weft and indicating the presence of a defect. This inspection is called preventive since it tends to limit the propagation of the defect. It requires total control over the production parameters. This method, although it seems to be optimal for fabric quality control, is difficult to implement for several reasons. Firstly, the knitting process is too complicated to stop and restart on time. Moreover, the production is slow enough to keep the human attentive to the detection of defects; the production speed of 0.3-0.5 m/minute makes such an activity boring and does not guarantee the concentration and effective occupation of the inspector [38]. The hostile industrial environment does not favor this method since the heat and noise produced by the knitting machines are unbearable for the inspector [38].

The second method is applied to the final product. It is therefore a post-production inspection. It consists of validating the quality of the final product to determine its quality category and thus make the appropriate decisions such as price, buyer, etc. It is easier to apply since there will not be the problem of stopping and restarting the production line and can be applied in a separate phase. The post-production inspection steps are the following [30]:

a. Pull the fabric rolls from the machines.
b. Roll the rolls onto an inspection shelf. This shelf is designed specifically for this task. It is specially designed for this task and operates at a relatively high speed (usually 8 to 20 meters/minute).
c. Apply human inspection. The inspector simply turns the tablet motor on and off depending on the presence of a defect to note its nature and location.
d. The result of this inspection is transformed into statistics which are analyzed to take the necessary measures to reduce the defects, based on the nature, occurrence, and

regularity of the defect. A reduction in the price of the screen can be applied by the factory.

It should be noted that these statistics are also used to make decisions that affect knitting machines, such as changing certain parts in these machines and applying additional maintenance or life span.

Traditional inspection is difficult to carry out, not only for technical reasons but also for economic reasons. A study by Nickolay and Schmalfu

[45] shows that investment in an automatic tissue inspection system is

It is economically attractive when the reduction of personnel costs and the associated benefits are considered.

3.4 AUTOMATIC INSPECTION OF FABRIC

Automatic tissue inspection is based on computer processing. The only means that allows this inspection is the image. In essence, an automatic fabric inspection system takes images of the weft being produced and performs processing on these images to detect anomalies. Figure 3.2 shows the typical architecture of an automatic fabric inspection system.

The parallel cameras allow images of the weft to be acquired during production. The number of cameras varies depending on the type of fabric being produced and other technical specifications of the cameras. The parallelism aspect of the cameras generally allows a richer and faster acquisition. The width of the weft of fabric is generally the same as the width of the fabric itself.

This is usually between 1.5 and 2 meters [38]. A single camera can then obtain a detailed image and some small defects can interfere with the detection. The illumination system located below the tissue winder allows for a better image acquisition condition. In addition, the light parameter is very important. Too much light or too little light will result in an unclear image which may mislead the computer, in which case a false dye fault alarm may be triggered. The illumination system is manipulated by a special controller to set the illumination of the system according to the nature of the fabric or the overall illumination of the plant.

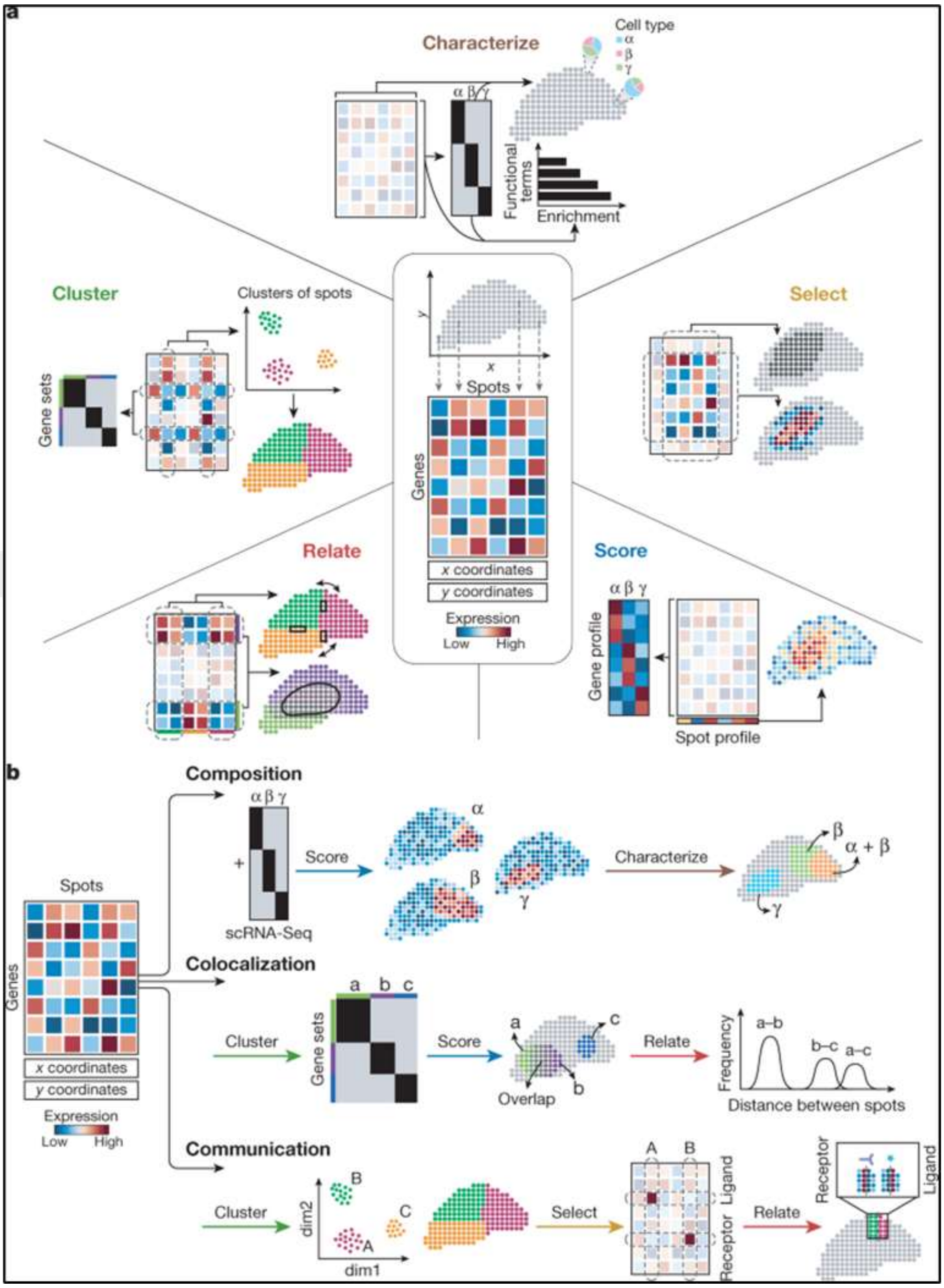


Figure 3.2: Architecture of a Typical Automatic Tissue Inspection System [42].

After the images have been obtained, they are moved to a device that is responsible for image acquisition. This device enables the data to be gathered in pixel format, which ultimately results in an overall image that has the desired richness and a high resolution.

The essential processing is carried out by the computer on these images in order to identify the flaws and, ideally, to categorize them according to the nature of the flaw, the type of flaw, and the size of the flaw. The defect map and the defect statistics report will be the products of this task. The defect map will show the geographical coordinates of the defects that are present in the fabric, and the defect statistics report will be evaluated by management in order for them to make the appropriate decisions.

The texture of the fabric is what classifies it as a textured substance. Therefore, if there is a problem with the fabric, the problem should be with the pattern. According to the research [42], there are three different categories of textured materials. These categories are pattern textured materials, randomly textured materials, and consistently textured materials. Figure 3.3 shows examples of the different classes of textures. In our work, we focus on uniformly textured fabrics, but the approach can be easily extended to deal with patterned materials.

Figure 3.3 shows the different texture classes in textured materials. According to the state of t h e art of texture detection, to deal with the problem of automated detection of defects in uniformly textured fabrics, there are three types of approaches, as shown in the same figure.

3.4.1 Statistical Approaches

Statistical approaches are based on a common assumption; that gap-free regions have stationary statistics and are talented over a large area of the picture. From this assumption, researchers conclude that any region that admits different statistics than the gap-free regions (which we have identified) will be a good candidate for the new statistical approach.

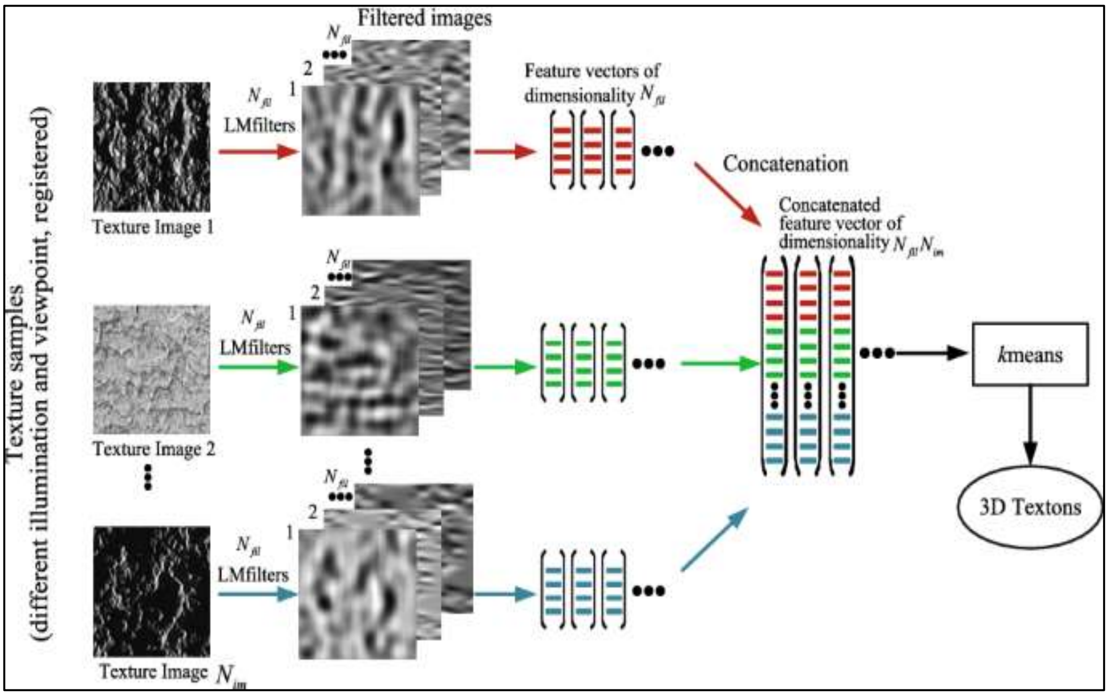


Figure 3.3: Classification of Texture Materials and Texture Defects Detection Approaches [42].

In this case, the region called the healthy region) is a faulty region. The statistics used in this type of approach are multiple, such as the image histogram [46, 47, 66], the fractal dimension [22], first-order statistics [47, 24], cross-correlation [13], edge detection [23, 40, 43], morphological operations [66], the co-occurrence matrix [24, 59], eigenfunctions [61, 1], order functions [5, 6], and the use of the image histogram [46, 47, 66].

[26] and linear transformation functions [2]. In addition, statistical approaches constitute a large volume of the methods used in the field of texture fault detection [42]. The results achieved by these approaches are satisfactory. As an illustration, in [22], the authors used the fractal dimension to detect texture faults. In addition, the

The fractal dimension makes it possible to detect the similarity between a set of data defined in a space of defined dimensions and a set of its copies.

o N_r is the number of copies of the data set and r is the reduction dimension.

This generic approach can be applied to texture classification, or even texture segmentation since the latter represents the selection of a set of characteristics. Therefore, if we define a block of the texture image as a healthy block and consider the rest of the blocks in the image As long as there are copies of this healthy block, we can calculate the fractal dimension of each block.

3.4.2 Spectral Approaches

Following this, spectral methods are introduced for the purpose of the identification of texture faults.

The evaluation of statistical methods has revealed that there are some shortcomings. It is possible for a texture to have more than one sort of flaw at the same time without the statistical properties being affected. Because of webs in the fabric, the researchers found that the most fundamental pattern primitives had a high periodicity. After that, the utilization of this periodicity enables the identification of texture defects. Researchers have utilized fruitive transforms such as the Fourier transform, the discrete cosine transform, and spatiofrential transforms such as the discrete wavelet transform to accomplish this goal. [42].

These methods have been used in the literature and have produced satisfactory results in the detection of faults. One of the methods that have given good results in the detection of faults in fabrics is the independent component analysis (ICA) [80the authors used this method to discriminate textures. This method is essentially based on the composition of the native texture (a sample of the healthy texture) into a set of source textures (the textons). To better explain this method, we make an analogy of a music piece in which several instruments are played. The goal of this method is to decompose this piece into a set of source signals, where each source signal represents the music played by a given instrument, and the union of all the source signals produces the music piece in question.

The number of sources that produce the different signals is the number of sources. By analogy to the example given, the texture is formed by a set of textons. Once the source textures are estimated, they form a source texture base and any sample of this texture can be composed on this source texture base. Thus, it becomes obvious to classify each sample according to the source textures exhibited.

Modelling-based approaches

Probabilistic models have been incorporated into image processing as a result of modeling-based techniques. In most cases, the texture is regarded as a complex model, and it is possible to characterize it using either a stochastic or a deterministic model [42]. According to Cohen and Fan [20], real-world textures, such as the texture of fabric, can be represented as stochastic processes.

The analysis of realizations, also known as samples, from probability distributions mapped onto the image space forms the foundation of this technique. The overarching presumption underlying these methods is that it is feasible to summarize the texture in the form of a statistical model. This model is what we refer to as the "compact signature" of a particular material. Textured regions that have the same appearance are represented by two models that are very similar to one another. As a result, the challenge of locating errors transforms into the problem of contrasting models, which is a problem that is significantly simpler to resolve. Maximum likelihood and Kullback-Leibler (KL) divergence [4] are just two of the many techniques that have been utilized and successfully implemented in order to make a comparison between the two models. The Gauss-Markov algebraic field modeling is one of the approaches that has seen the most use throughout the research community. Gauss-

Markov random fields were utilized by the authors in order to model the texture in [25], while this model was utilized by the authors in order to identify defects in the texture in [21].

3.5 EVALUATION CRITERIA FOR TEXTURE FAULT DETECTION ALGORITHMS

In any algorithm developed, it is necessary to evaluate the method used objectively. In the computer science field in general, any algorithm produced is valued by indicators that change from one context to another. Among these criteria, we can mention complexity, accuracy, optimal use of resources, etc. In the field of automatic fabric inspection, there are no standard criteria for evaluating texture detection methods. In fact, in each work published in the past, the authors use customized criteria to evaluate their methods. Although these criteria appear to be theoretically viable, their variety and different customizations do not allow for a comparison of these methods or objective evaluation. In addition, most of the work done has been tested on different databases.

This limits the possibility of visually comparing the results of different algorithms. The third problem is the limited expression of the results of a method. In fact, in several works (e.g. [22]), we note that the data set is limited and there is no reference to experiments in paper or electronic appendices.

In the following, we will quote some of the previous works. In [22], the authors achieved a detection rate of 96%, but the accuracy is poor and false alarms are very high. We, therefore, note that the criterion that has been taken into consideration concerns only the faulty blocks. The correct treatment of healthy blocks was not taken into consideration. Therefore, the false alarms were ignored even though they induce

The loss of the plant is because healthy tissue is detected as defective. This has a profound effect on the decision regarding a native product frame. In addition, the data set used in the work is very small (16 images, 8 without defects and 8 with defects), which is insufficient to evaluate this method.

In [57], the authors expressed detection rates of 96%, while in subsequent works [56], they indicated rates of 92%. In addition, the evaluation criteria of their algorithms were customized and changed f r o m one paper t o another. In fact, in the first works [57], the authors were not very precise and the evaluation was expressed in terms of the percentage of this criterion. In other works [56, 58], this criterion no longer appears. On the other hand, in these works, the evaluation is based on the number of blocks not correctly defined in a global set of blocks of a given size.

3.5.1 The Wavelet Transform

The two-dimensional discrete wavelet transform (DWT) allows the representation of an image in the spatial-frequency domain. It is based on multi-run analysis that hierarchically decomposes a signal (image) into two parts. The first part, of low frequency, is a kind of average of the original signal commonly called an approximation image. The second part is a set of sub-bands constituting the details of the image; at each resolution level, the details are organized as 3 sub-bands oriented horizontally (H), vertically (V), and diagonally (D). These details are commonly referred to as wavelet coefficients.

Wavelets were originally introduced by Alfred Haar in 1909. They were applied to represent one-dimensional signals. Mallat [44] extended the application of the wavelet transform to images (or two-dimensional signals). He thus introduced the fast wavelet composition/reconstruction algorithm. This algorithm is cursive and is essentially based on two operations:

a. Filtering: convolution of the signal with a low pass filter (h0) or a high pass filter (g0).
b. Subsampling: reducing the number of samples in the signal. Horizontal undersampling (1:2) of the image is equivalent to eliminating every other column, which reduces the number of pixels per row by half.

The algorithm of [44] is such mantis in Figure 3.1 and is explained as follows:

Let Sj be the one-level approximation image of r solution j and let DX be the subbands of orientation X, o X ∈ {H, V, D}, extracted at r solution j. As shown in the figure, the image Sj passes into the input of the algorithm. It undergoes both high-pass and low-pass processing. The two resulting images are downsampled on the lines. The two downsampled images are each filtered by a high-pass and a low-pass filter to produce 4 images. The latter are subsampled again, giving 4 images of the same size: an approximation image (Sj+1) and 3 images of DX j+1, X ∈ {H, V, D}.

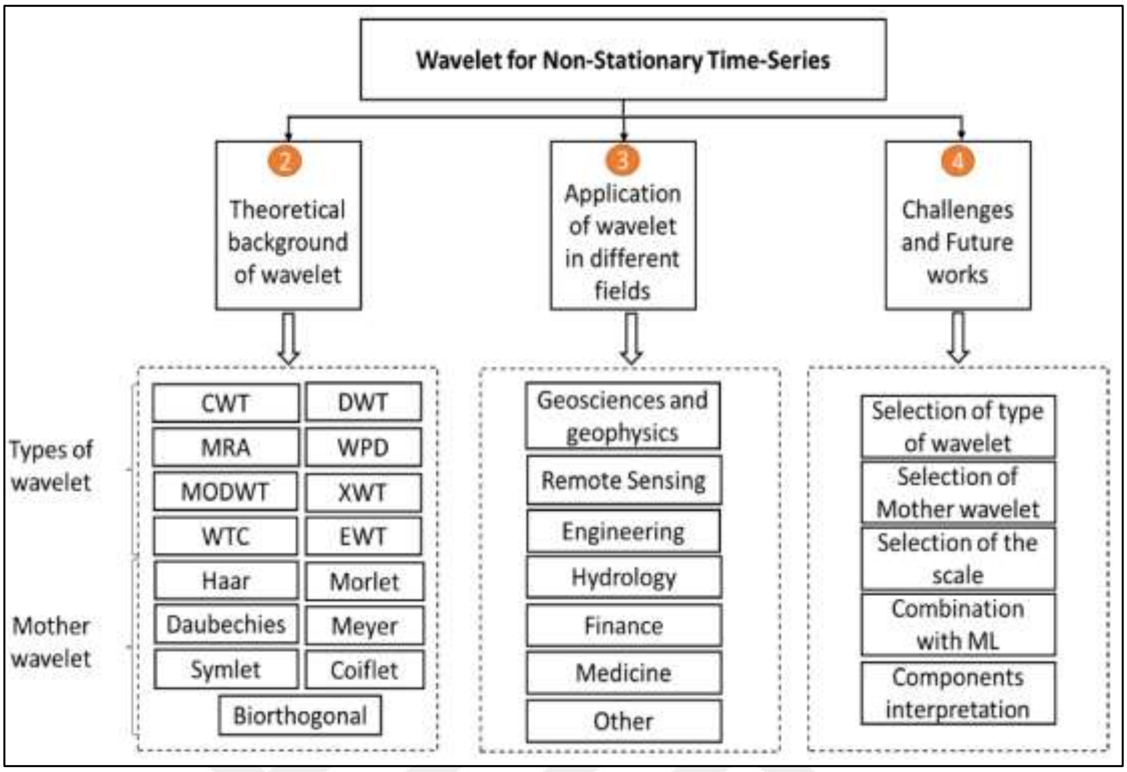
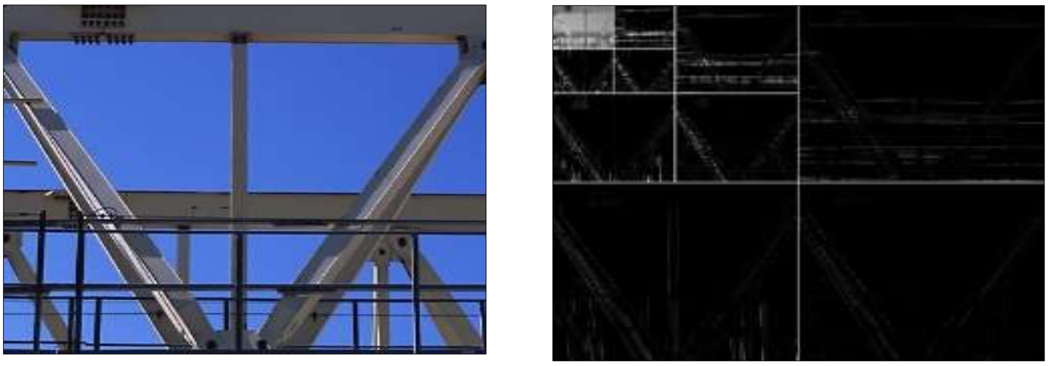


Figure 3.4 Wavelet Cursive Composition Scheme and the Obtaining of the Four Sub-Bands.

The wavelet transform has several other benefits, one of which is that it is a fast algorithm for compositing and reconstruction. Additionally, the wavelet image representation is compact because the total number of wavelet coefficients is equal to the number of pixels in the associated picture. In contrast to the coefficients that are produced by the Fourier transform (FFT), which are complicated, the coefficients that are used in wavelet analysis are real. The reconstruction of the image from its wavelet representation should also be observed to be paralleled by the reconstruction of the image from its wavelet representation.

This shows that all the information in the image is retained in the wavelet transform. We present in Figure 3.2 an example of the application of the three-level wavelet transforms on a natural image.



(a) Original Image (b) 3-level Wavelet Composition

Figure 3.5 Example of applying the 3-level wavelet transform to a natural image.

Wavelets have a limited ability to represent directional information in the image, which results in a weakness in the detection of smooth contours. This limitation is due to the limited number of orientations captured by the wavelet filters during compositing. The wavelet subbands have either a horizontal, vertical, or diagonal orientation. Moreover, the diagonal subbands of the wavelets are usually ignored in wavelet transform-based processing. The information contained in the diagonal sub-bands is considered irrelevant (considered as noise).

3.5.2 The Laplacian Pyramid

The Laplacian pyramid was introduced in 1983 by Peter J. Burt and Edward H. Adelson [18]. The goal of the researchers was to find a technique that would remove the high correlation between a pixel and its neighborhood. This allows a better coding of the image since it ensures the optimization of the number of bits necessary for the encoding. This technique combines the characteristics of prediction and transformation methods while maintaining the simplicity and locality of the calculations. The prediction technique is relatively simple to implement and is considered to be adapted to the local characteristics of the image. The transform in turn allows for better data compression while keeping the computation time reasonable [18].

Suppose that we are going to compute the Laplacian pyramid of an image S0 (i, j). To do so, we apply low-pass filtering followed by a subsampling rate of 2 according to each dimension to obtain a low-pass filtered image that we note S1 (i, j) and whose total size is reduced by 4 compared to the original image S0 (i, j). The prediction error image that we note L0 (i, j) is obtained by the following equation:

$$L0\,(i,j) \;=\; S0\,(i,j) \;-\; S1j\,(i,j) \tag{3.1}$$

The image S_1^J (i, j) *is* an interpolated version of S_1 (i, j) and thus has the same size as the image

S_0 (i, j). In turn, the image S_1 (i, j) is low-pass filtered and subdivided into two parts

The first image is sampled to give an image S_2 (i, j). Thus, a second prediction error image noted L_1 (i, j) is computed by adapting equation 3.1. By repeating this process, we obtain a sequence of prediction error images L_0 (i, j), L_1 (i, j), L_2 (i, j),... L_n (i, j) such that the size of each image is a quarter size of its predecessor. This sequence is the Laplacian pyramid of image S_0 (i, j).

Instead of encoding the S_0 (i, j) image, it is better t o encode L_0 (i, j) and S_1 (i, j). In f a c t, L_0 (i, j) is largely uncorrelated and its binary representation requires fewer bits than the S_0 (i, j) image. Moreover, the S_1 (i, j) image is low-pass filtered and can then be encoded as a single image.

a reduced sampling rate. Applying this process several times on the low-pass images denoted S_k (i, j), $k \in \{0, ..., n\}$, we benefit from the 2 advantages mentioned above several times in a cursive way.

The pixel values in each prediction error image in the pyramid correspond to the difference between two pseudo-Gaussian or related functions, convolved with the original image. The difference between these two functions is similar to the Laplacian operator commonly used in image enhancement [53], hence the name Laplacian for this pyramid. In Figure 3.3 we show the operation of the Laplacian pyramid algorithm to produce the approximation and prediction error (part (b)) as well as the final result of this algorithm (part (a)).

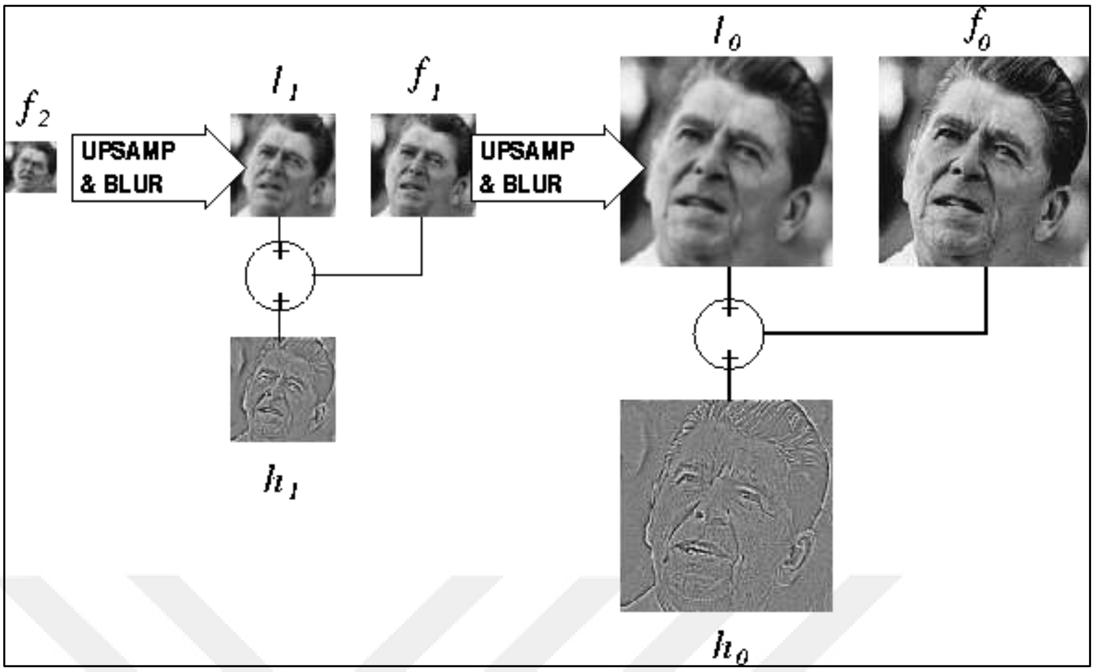


Figure 3.6 Composition in Laplacian Pyramid.

3.5.3 Two-dimensional Directional Filtering

The contourlet transform allows for a small and flexible number of directions at each Laplacian level while reducing the near-critical sampling. This is achieved by using a bank of two-dimensional filters that have different orientations. With such a rich set of basis functions, the contourlet transform can represent a smooth contour with fewer coefficients compared to the wavelet transform. In addition, the contourlet transform uses regular filter banks, which makes its algorithm fast and efficient [51].

In order to provide a clearer explanation of what we have accomplished, we have provided an example in Figure 3.4 of the implementation of the wavelet transform and the contour-letter transform on an image. This example demonstrates how the wavelet transform and the contour-letter transform function. In this section (a), five instances of 2-D wavelet-based images are presented. The examples of four contourlet-based pictures are provided in the following section (b). In part (c), we present an illustration that demonstrates how wavelets with square supports are unable to capture discontinuity points. In contrast, contourlets with elongated supports are able to capture linear segments of the contours and, as a result, are able to successfully capture the edges of the contours.

to represent a smooth contour with fewer coefficients [51].

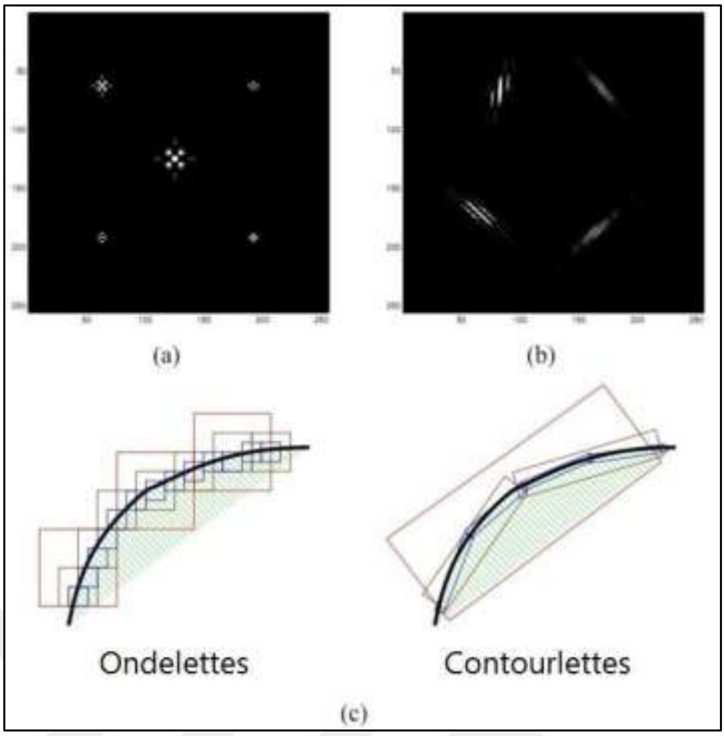


Figure 3.7 A representation of the Operation of Wavelets and Contourlets for Images [51].

Figure 3.5 shows the edibility aspect of the number of directions for each solution level. In addition, the figure is a contour-lined fringe representation with 4 solution levels (L = 4) and the different fringe directions for each solution level; the first and second solution levels have 4 directions while the third and fourth solution levels have 8 directions. The approximation image (low frequencies) does not undergo directional de-composition. We also notice that the number of directions is always a power of 2 ($8 = 2^3$ and $4 = 2^2$).

In Figure 3.6, we show the execution of the contour transform algorithm.

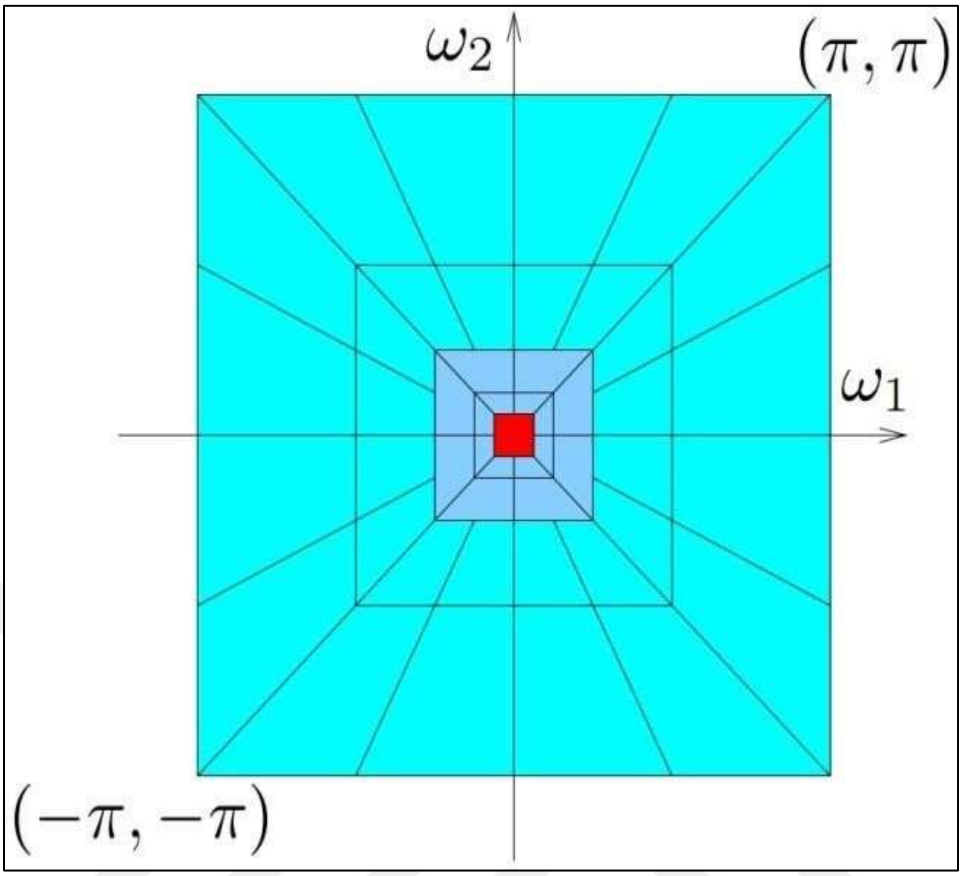


Figure 3.7 A Common Representation of the Contourlet Decomposition with 4 Levels of Solution (L = 4).

(a) is a representation of the image that is used as an input to the algorithm that performs the contourlet transform, and (b) is a representation of the image after it has been transformed using the contourlet algorithm. (a) is a representation of the image that is used as an input to the algorithm that performs the contourlet transform, and (b) is a representation of the image after it has been transformed using the contourlet algorithm. At first glance, it is obvious that the transform in question is a 2-level contourlet, with L set to 2. Additionally, we observe that the first level allows for the admission of four frequent directions, whereas the second level allows for the admission of eight frequent directions.

In this example, the Laplacian pyramid has 2 levels and 1 approximation. The bench of contourlets has subdivided L_0 into 8 sub bands (2 levels). L_1 is subdivided into 4 sub bands (1 level) and the approximation image is subdivided into 4 sub-bands (also 1 level).

3.5.4 The Transformation Into Redundant Contours

Following a contour image composition, it is clear that the resulting bands are not all the same size both on the same solution level and across the different solution levels.

When dealing with a cooperative processing of different sub bands of a contourlet, it is desirable to have sub bands of the same size in order to avoid interpolation and mapping problems between the different levels of solution. Based on this requirement, a new variant of the contourlet transform was born under the name of redundant contourlet transform [9].

We have shown in part 2 that redundancy comes from the Laplacian pyramid and can reach an oversampling rate of up to 1/3 giving a total storage space of 4/3 of the original image size. More redundancy can

This is achieved by eliminating any undersampling operations in the Laplacian pyra-midal system; using L appropriate low-pass filters to create L low-pass approximations of the image. The difference between each approximation and its later low-pass version is an image bandwidth. The final result is a Redundant Laplacian Pyramid (RLP) system with L+1 equalsized levels, a coarse approximation image and L bandpass images. Each bandpass image is filtered by a directional filter bank (DFB). The filtering performed is a two-dimensional filtering and

the directional filters are pseudo-Gaussian filters. The redundancy factor is d -

By applying the same principle on the d-directional composition level with critical sampling on each PLR bandwidth, we obtain a redundant contourlet trans-form with L * D directional sub-bands of sizes.

The symbol D represents the number of digits of the image, in addition to the magnified approximation image. The symbol D represents the number.

In this case, the contourlets are composed of the desired directions, and each contourlet sub-band is represented by a sub-image.

In Figure 3.8, we present the application of the redundant contourlet transform on the same image of Figure 3.6. Part (a) shows the image input to the redundant contourlet transform algorithm, while part (b) shows the sub bands of the transform.

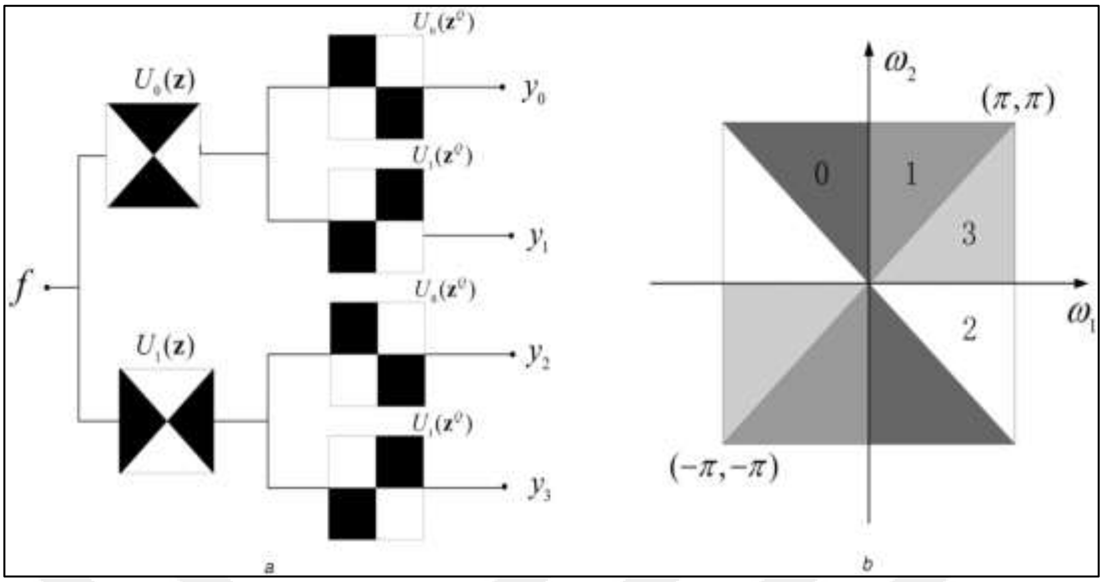


Figure 3.8 Example of the Application of the Redundant Contourlet Transform.

4. PROPOSED METHOD

4.1 CHAPTER INTRODUCTION

In the past decade, there has been a general increase in the processing capacity of computers, which has facilitated the study of artificial neural networks. Processes that were once thought to be impossible to solve, such as natural language processing, are now producing results that are comparable to (and in some cases even superior to) what people can achieve. Several different disciplines, including medicine, robotics, business, and biology, have made significant strides in their application of machine learning thanks to the rapid development of deep learning methods. In specifically, convolutional neural networks have demonstrated excellent performance in a variety of image processing tasks, including classification, segmentation, and object detection[1].

With the advent of Industry 4.0, the use of smart components, robots and IoT is increasingly common in factories [2]. This integration between the digital and physical environment in industry allows not only faster product development, but also mass customization (customized orders from customers go straight to the intelligent production line system), production flexibility and cost reduction.

For the textile industry, for example, quality control is vital, since a defect in the fabric tends to reduce its sale price by 45% to 65% [3]. Thus, a large number of manufacturing defects can significantly reduce the revenue of a textile producer, so it is extremely important that such defects are identified during production, as well as their causes [4].

Although vital, the process of inspecting fabrics tends to become extremely tiring for the employee (when done manually), given the production volume of textile industries and the repetitive nature of the work. Moreover, the manual inspection process is subject to human failure and productivity drop throughout the work shift.

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 [5]. 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 4.1 - in fabrics in a production line, beyond the classification of the detected print.

Figure 4.1 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 [6], which contains more than 90 thousand images.

4.2 THEORETICAL BACKGROUND

Artificial neural networks are strongly inspired by the biological functioning of nervous systems [7]. 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. $Output =$

$f(\sum \omega i X i)$ (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 2 below represents the behavior of this activation function.

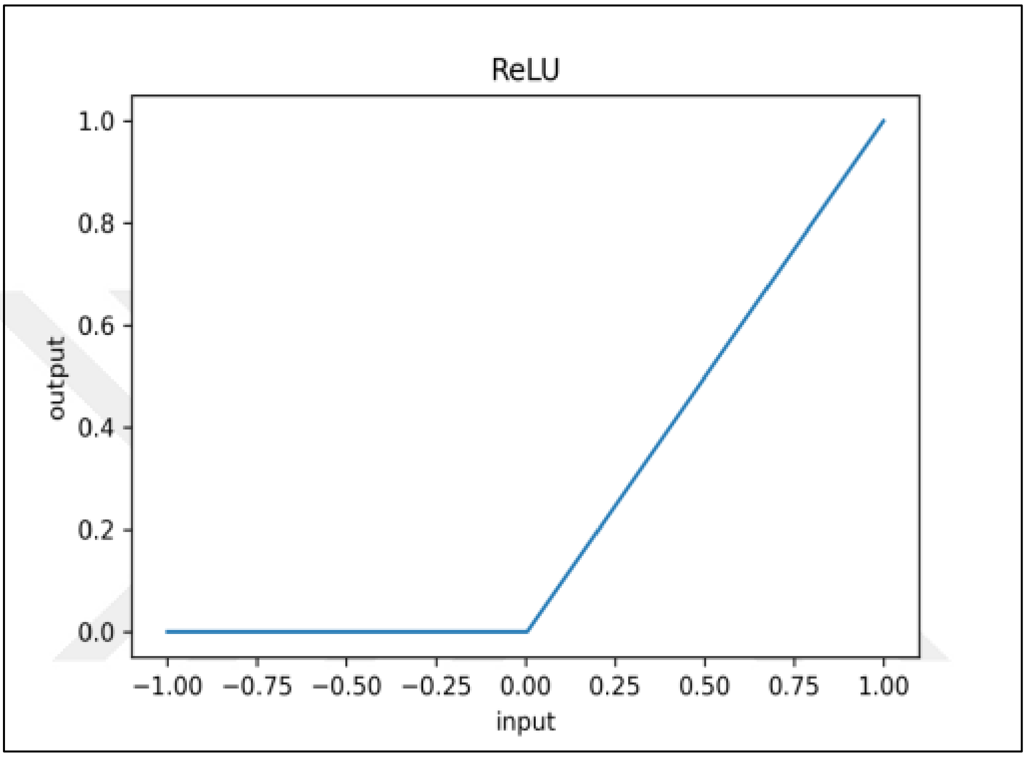


Figure 4.2: Behavior of the ReLU Function.

The concatenation of layers of neurons - where the first receives the *inputs*, and the subsequent layers receive the outputs of the previous layers - allows the model to have a large abstraction capacity, allowing it to learn representations of the data and identify patterns. These layers of fully connected neurons are called dense layers and this learning process with multiple concatenated layers is called *Deep Learning* [8].

CNNs (Convolutional Neural Networks) have some significant differences: since they use images as input, the *inputs* have three dimensions: width, height and depth - the latter representing the number of color channels (RGB) of the image, not the network depth - and three types of layers: dense layers, convolutional layers and *pooling* layers. Convolutional layers, unlike dense layers, receive as input only a portion of the *inputs* from the previous layer and return an *output* with lower dimensionality in width and height, but with greater depth (more channels). *Pooling* layers aim to reduce image dimensionality without significant loss of 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. These layers applied together allow the model to recognize patterns in the images and define spatial relationships between image elements. A representation of the general operation of a CNN can be seen in Figure 4.3.

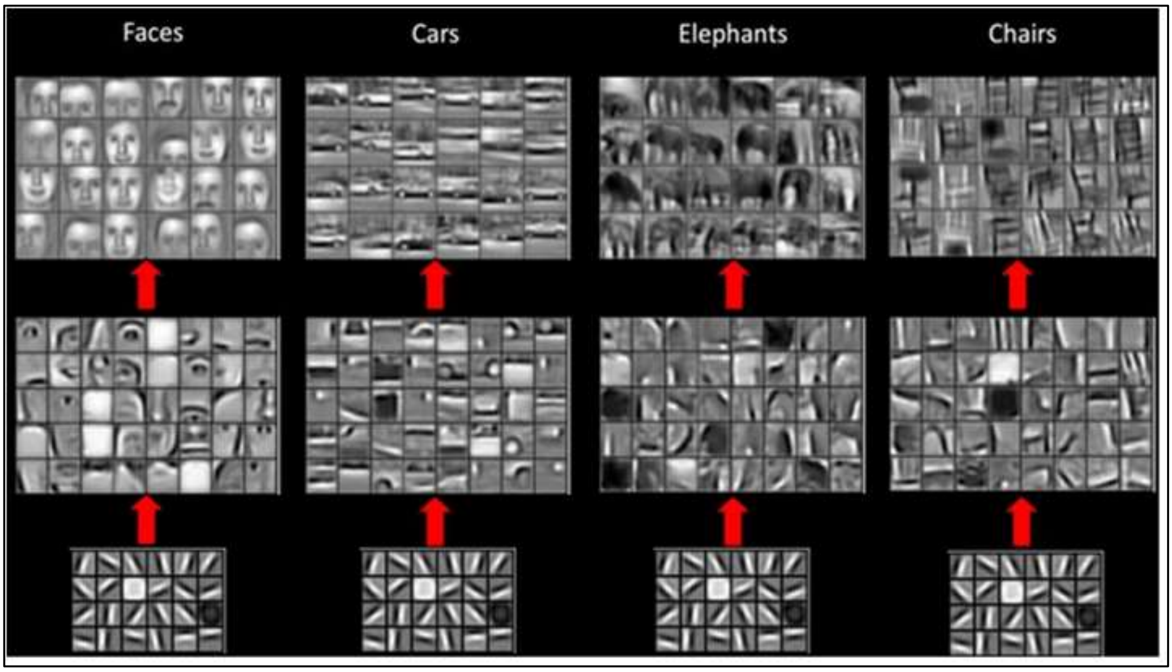


Figure 4.3: Visual Representation of the Layers of a CNN.

Detectors are a special type of CNN that seek to identify all object instances - of classes known by the model - present in the input image. This process is done by proposing regions of interest, called anchors, which are made for each of the pixels in the image [9]. The model then gives a score (called confidence value) for each of the classes in the proposed region. The m x n dimensions of this window are then adjusted, based on regression, and the process is repeated. Naturally, this process returns multiple detections of the same object, given that several anchors detect the same object in the image - as can be seen in Figure 4.3. To solve this problem, non-max suppression is used [10], a method that analyzes detections with a high IOU (intersection over union, represented visually in Figure 4.4) - i.e., significantly overlapping - and discards all detections except the one with the highest confidence value.

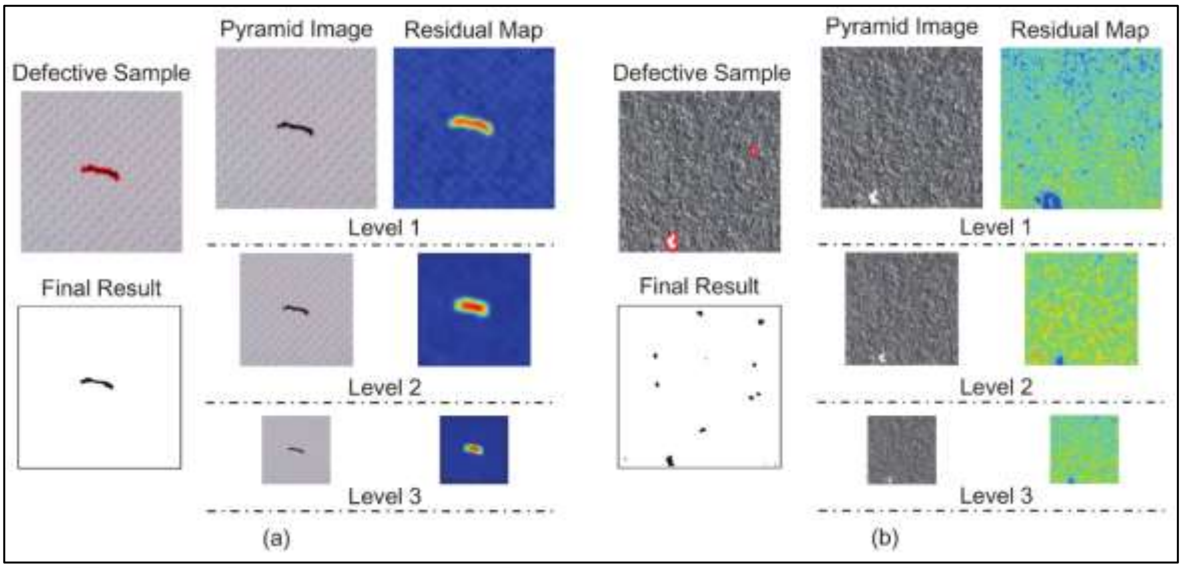


Figure 4.4: Anchors Before and After non-max Suppression.

One would typically expect that increasing the size (in number of neurons) and depth (number of layers) would result in better neural net performance; however, this is not true in all cases. Model error can increase due to some factors, such as overfitting (weights that are overfitted to the training set, so that the model loses the ability to generalize well to new data), and gradient vanishing (the vanishing gradient, whose value is used to readjust net weights during training). Gradient vanishing is caused by the fact that many activation functions (like the sigmoid in Figure 5) flatten the input space to values between 0 and 1, so that a variation in the input tends to generate a very small variation in the output, and therefore the derivative (used in computing the gradient) will be very small as well. This effect is potentiated with the concatenation of layers, impairing the training [11].

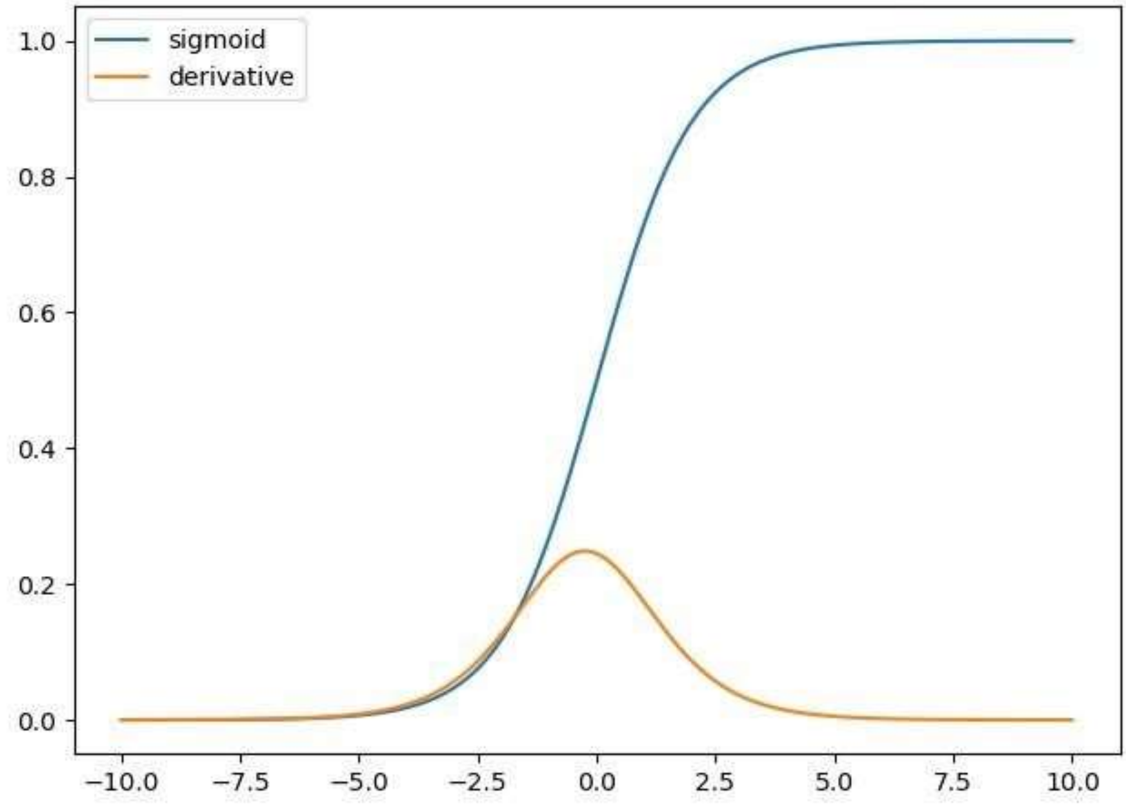


Figure 4.5: Sigmoid Activation Function and its Derivative.

Many approaches have been suggested to circumvent this problem, and for this work the approach chosen was to use a ResNet [12](residual neural network). Residual networks significantly mitigate the impact of the gradient vanishing, due to the fact that the input is fed back after a certain number of layers, as shown in Figure 4.6. The logic block represented in the figure is then concatenated with other similar blocks, so that regardless of the depth of the network, the input will always be fed back every N layers (defined in the model architecture).

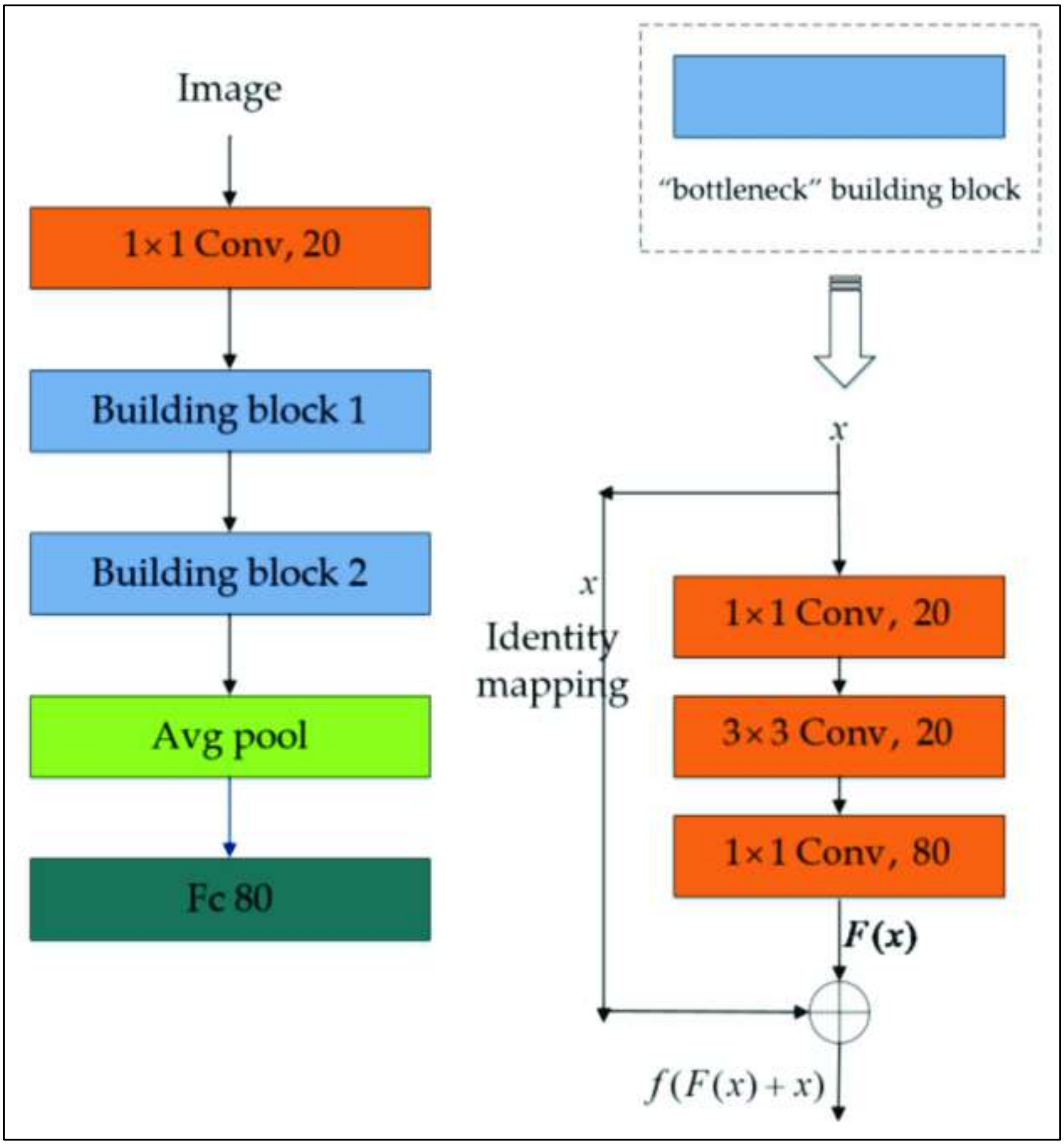


Figure 4.6: Visual Representation of a ResNet Logic Block.

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 [13]. 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.

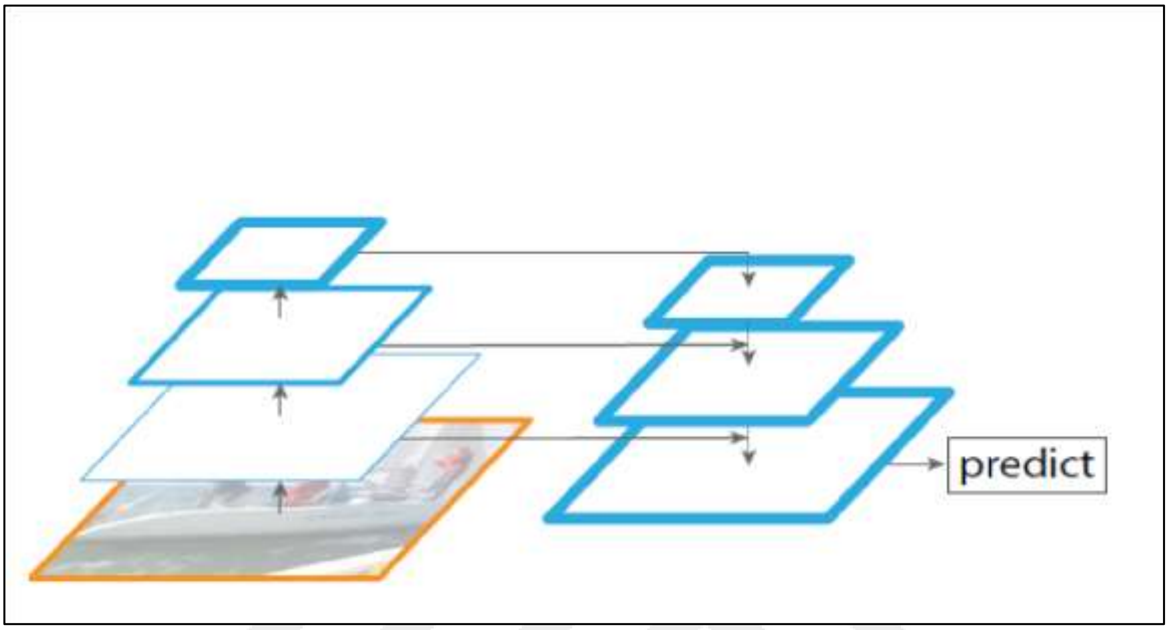


Figure 4.7 : Visual Representation of the Characteristics Pyramid.

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[14], 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 [15], 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.

4.3 PROPOSED METHODOLOGY

The dataset used was a ZJU-Leaper [6] 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.

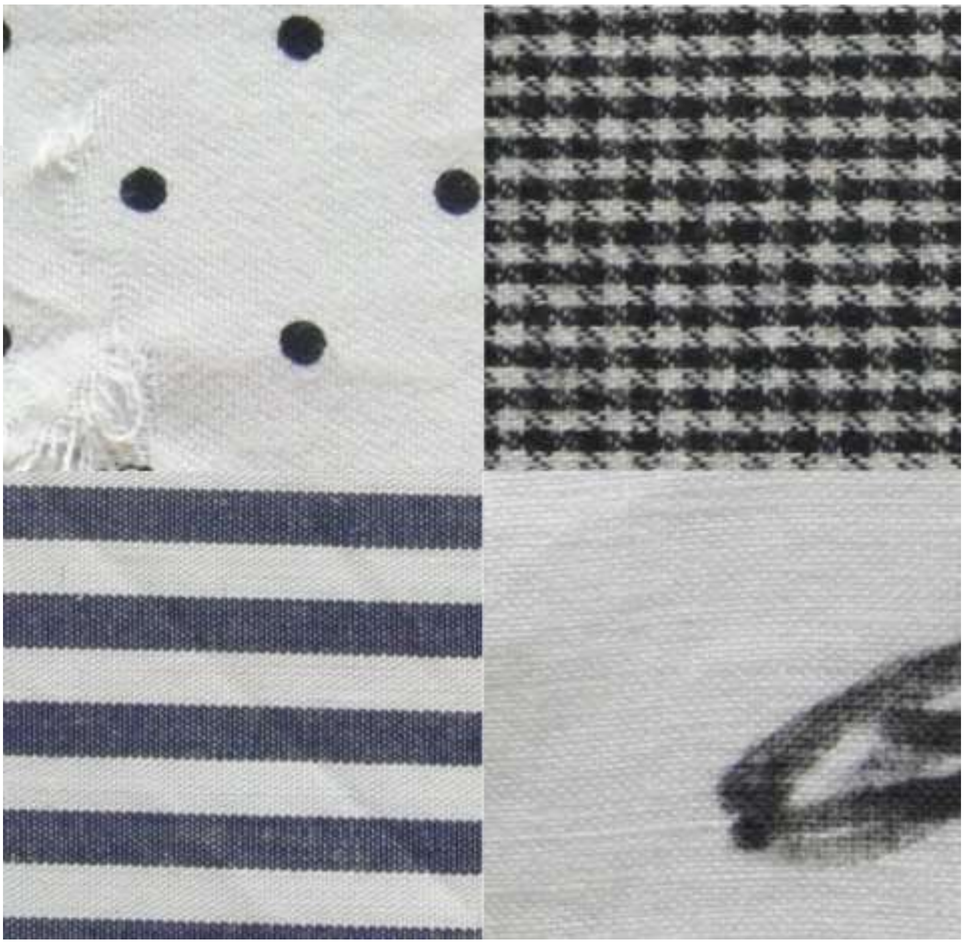


Figure 4.8: Examples of Images Present in ZJU-Leaper.

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 [21] (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.

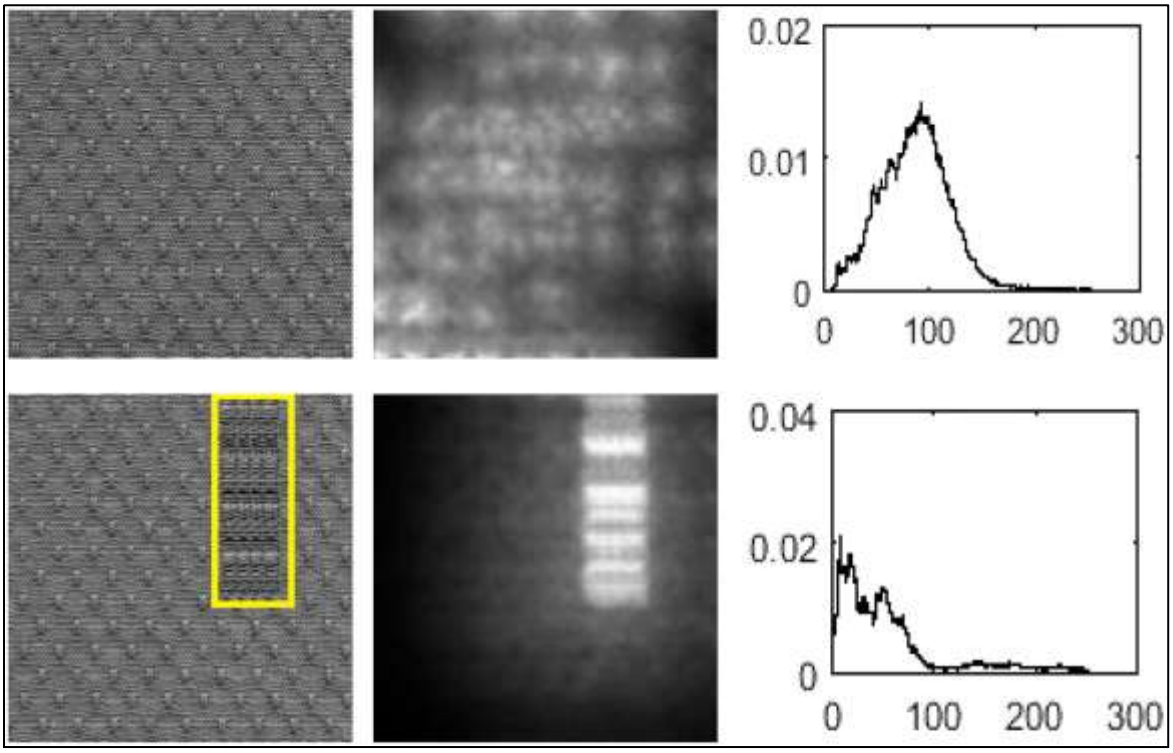


Figure 4.9 : Example of Annotation on CVAT Interface.

Making the annotations is a time-consuming and high-cost task, since it requires human labor - sometimes specialized in the task that the model intends to perform - to perform it. However, the quality of the annotations is directly linked to the performance of the algorithm [22].

The 756 images were then divided into 2 sets: 80% of the samples for training and 20% for validation. The training set is the one in which the model receives not only the inputs but also the expected outputs; through training, the model adjusts the weights through backpropagation, correcting the weights of each layer retroactively based on the errors of its predictions. The validation set is useful for analyzing the model's performance in new cases, given that in training the model did not have access to the expected outputs of this data. The metrics in the validation set are therefore the real gauge of model performance, given that the proposed operation consists in analyzing new data.

The metric used for comparison between the proposed model and the models presented by the dataset creators was the F1 score, which consists of the harmonic mean of precision and recall . In the equations below, the variable TP refers to true positives, FP to false positives and FN to false negatives using the API (Application Programming Interface) of Detectron2 [24], a Python library that allows easy implementation of state-of-the-art object detection algorithms. This library also automatically calculates mAP (mean Average Precision), a widely used metric in object detection. Average Precision (AP) is defined as the area under the precision-recall curve for a given IOU threshold [25] (for a minimum IOU threshold of 75%, the metric is called AP 75, for example); mean Average Precision is the average between APs calculated at different thresholds. These metrics allow analyzing not only if the model can detect or not the object, but also how good are the regions of interest proposed by the model - comparing mAP, AP 90 and AP 75 for example.

The RetinanetR101 FPN3x is implemented using a backbone of RetinanetR101, which has 100 hidden layers, but adding Feature Pyramids, totaling over 57 million trainable parameters.

The transfer learning was done through RetinaNet weights when trained on imagenet [26], one of the largest public datasets of images, containing more than 14 million samples. Even with the content of the two datasets being quite different, this initialization of weights helps the identification of objects in general given the variety of classes present in imagenet.

4.4 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 4.10: 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 4.1: Metrics of the Model in the Validation Set.

1. Metric	2. Value
3. Accuracy	4. 0,84
5. Recall	6. 0,93
7. F1 Score	8. 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. Figures 4.11 and 4.12 show two good examples of predictions, and Figures 13 and 14 are examples of failures.

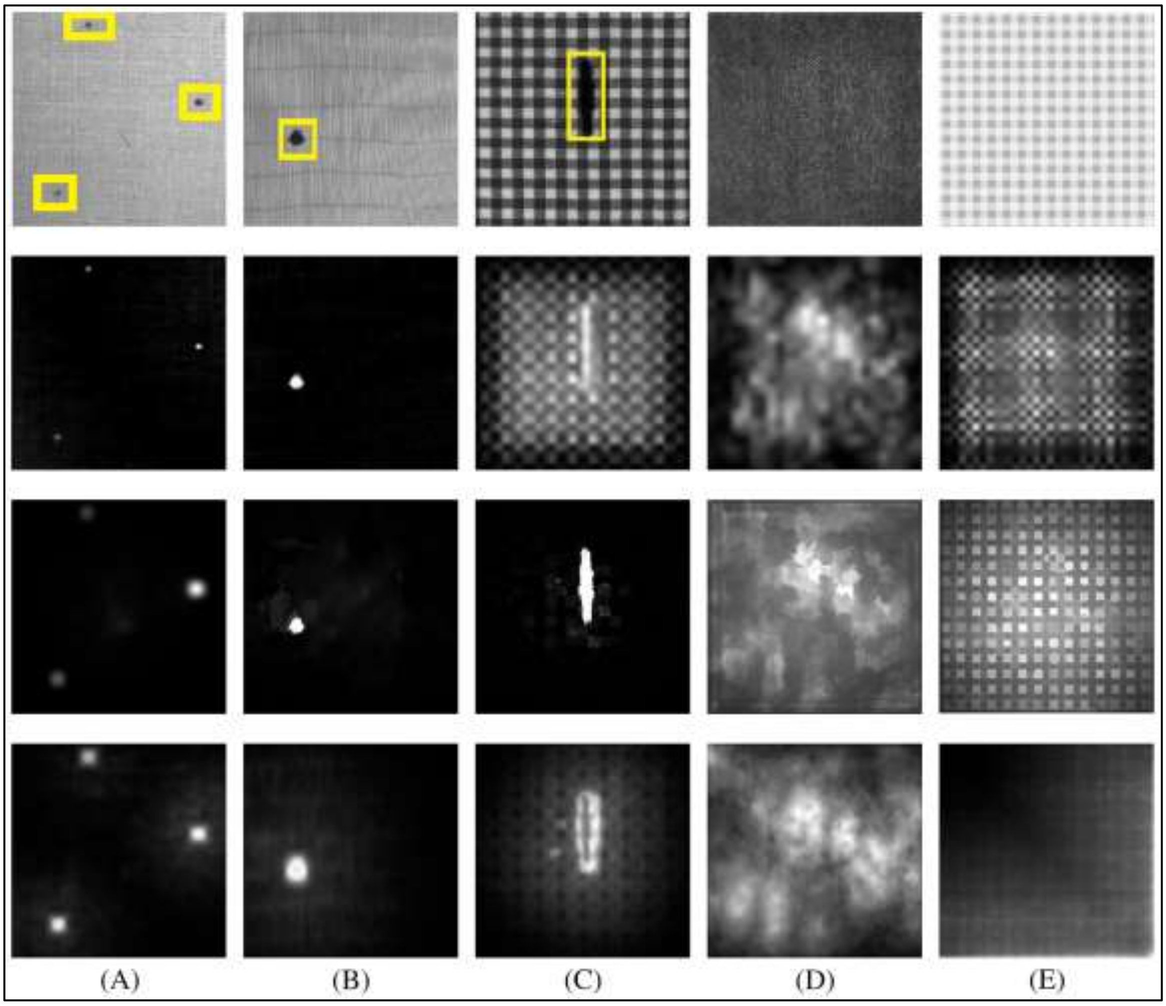


Figure 4.11 : Example 1 of Good Prediction.

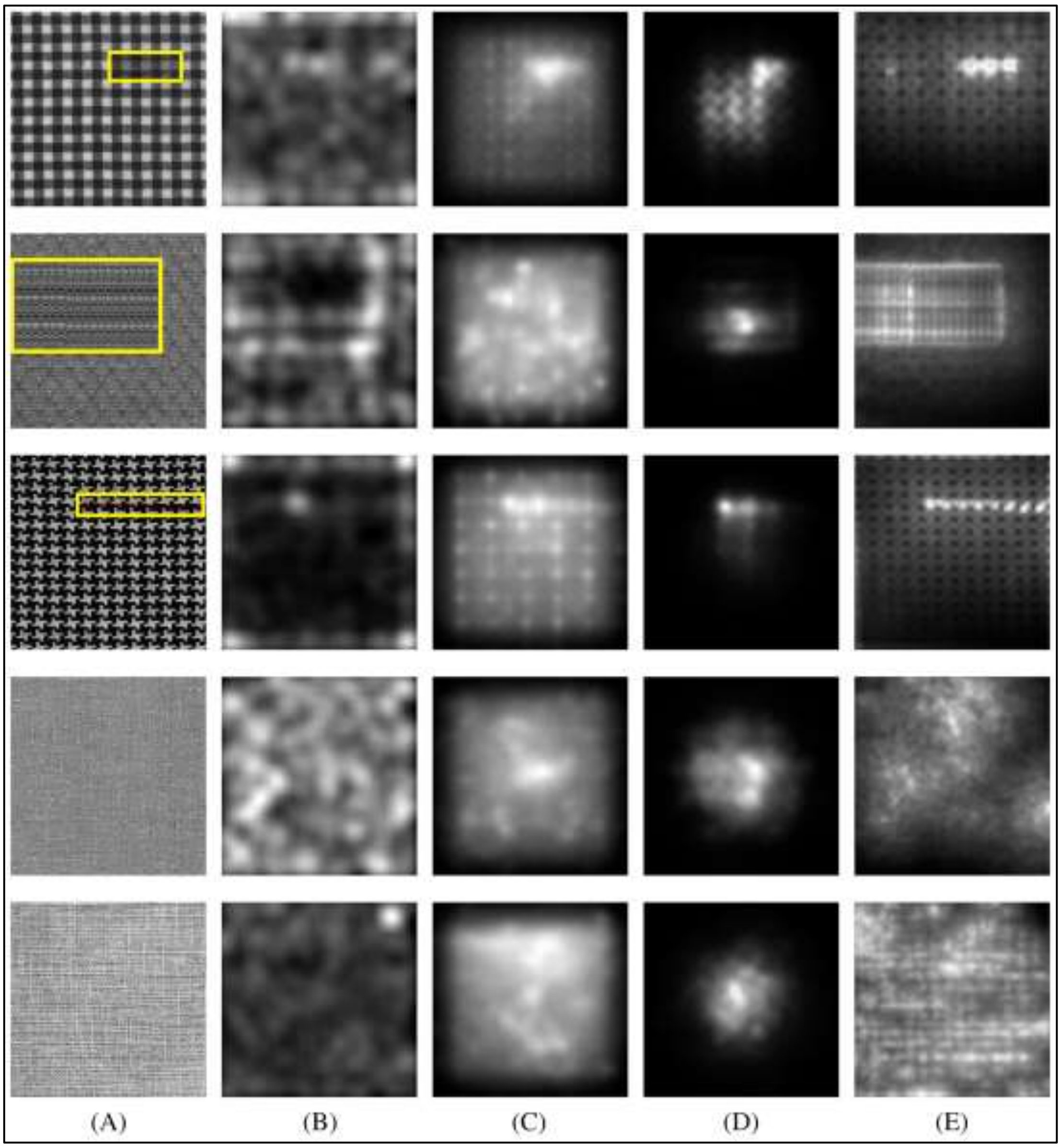


Figure 4.12 : Example 2 of Good Prediction.

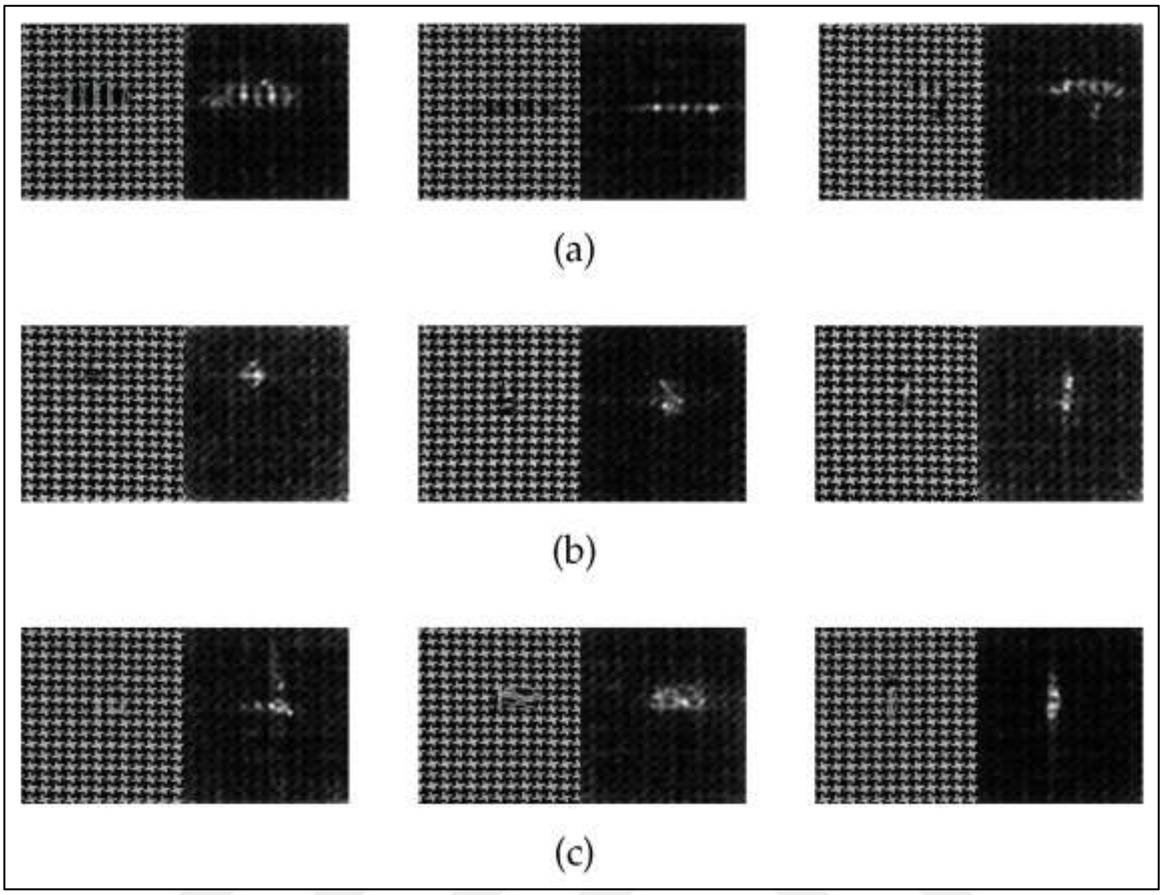


Figure 4.13: Example 1 of Poor Prediction.

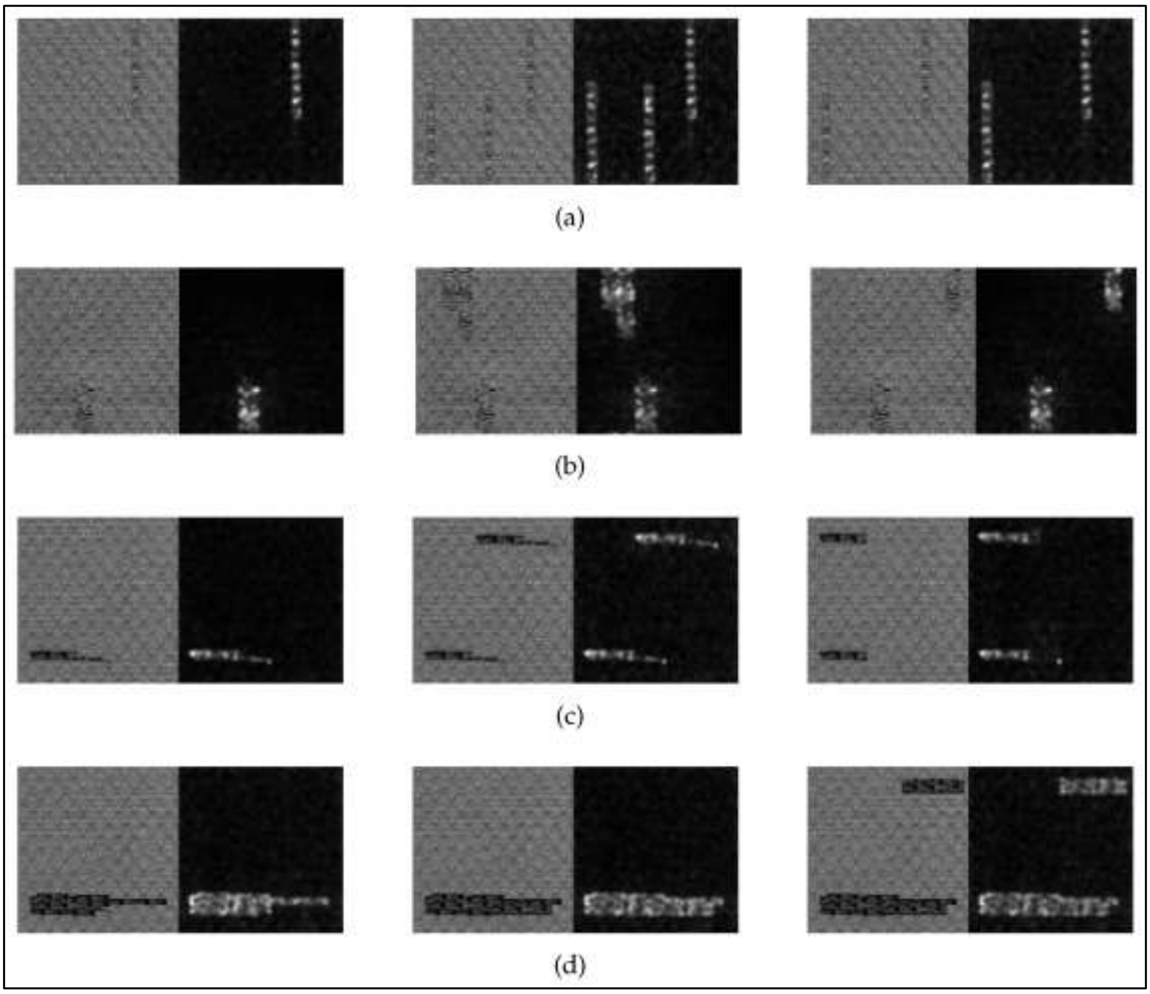


Figure 4.14: Example 2 of Poor Prediction.

Table 4.2 below presents the comparison between the F1 scores of the *baselines* proposed by the *dataset* authors
ZJU-Leaper [6] and the model proposed here.

Table 4.2: Comparison of F1 Scores Between the Proposed Model and the ZJU-Leaper Baselines.

Model	**F1 Score**
Sparse Coding	0,588
Convolutional auto encoder	0,187
One-class SVM	0,118
U-Net	0,558
U-Net(Transfer Learning)	0,906

It can be seen that the proposed model achieved the 2nd highest F1 score, second only to U-Net with masks annotations. However, this model is costly in terms of processing according to the authors themselves.

Among the related works, Jing et al. [19] 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 4.3 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 4.3: 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

As the Jing et al. model [16] only classifies one of the 81 image subdivisions, this high score comes at the expense of a good defect location. It is also noticed that the RCT-MoGG score is significantly higher than the others, showing the efficiency of the method to detect print patterns and then segment its noises.

The Detectron2 API also generates graphs of the mAPs over the model training iterations, as can be seen in Figure 4.15. 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.

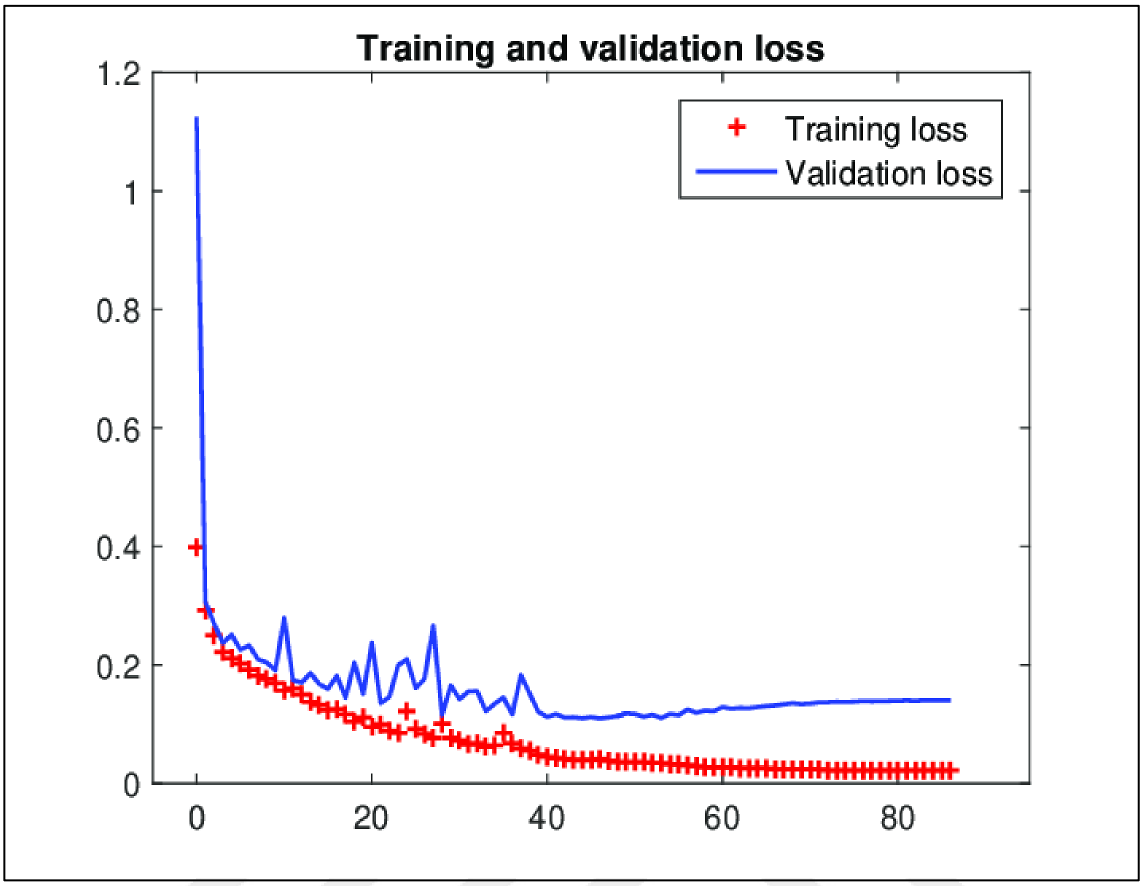


Figure 4.15: The Training Iterations of the Proposed Unet Model.

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.

Two of the related works informed the inference execution time, and these are represented in Table 4 in comparison with the proposed model. However, both models used 256x256 pixels images as inputs, while in this project the inputs used were 512x512. Thus, each 512x512 image has four times more data to be processed. Therefore, the amount of inferences per second of the proposed model will be multiplied by 4, as an estimate for the amount of inferences per second in the same dimension of the other models, to make the comparison more fair.

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. 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.

REFERENCES

[1] J. Lee, Industrial AI, Springer Singapore, Singapore, 2020.

[2] K. Yan, L. Liu, Y. Xiang, and Q. Jin, “Guest editorial: AI and machine learning solution cyber intelligence technologies: new methodologies and applications,” IEEE Transactions on Industrial Informatics, vol. 16, no. 10, pp. 6626–6631, 2020.

[3] K.-D. (oben, S. Wiesner, S. Wiesner, and T. Wuest, ““Industrie 4.0” and smart manufacturing—a review of research issues and application examples,” International Journal of Automation Technology, vol. 11, no. 1, pp. 4–16, 2017.

[4] A. Kumar, “Computer vision-based fabric defect analysis and measurement,” in Computer Technology for Textiles and Apparel : Woodhead Publishing Series in Textiles, J. Hu, Ed., pp. 45–65, Woodhead Publishing, Cambridge, UK, 2011.

[5] X. Xu, D. Cao, Y. Zhou, and J. Gao, “Application of neural network algorithm in fault diagnosis of mechanical intelligence,” Mechanical Systems and Signal Processing, vol. 141, p. 106625, 2020.

[6] J. Bullon, A. Gonzalez Arrieta, A. Hern ´ andez Encinas et al., ´ “Manufacturing processes in the textile industry. Expert Systems for fabrics production,” ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal, vol. 6, no. 4, pp. 15–23, 2017.

[7] M. Sibly Sadik, Defects of Woven Fabrics and <eir Remedies, Bachelor of Science, Department of Textile Engineering, Daffodil International University, Dhaka, Bangladesh, 2014.

[8] K. Singh, J. Kaleka, and J. Kaleka, “Identification and classification of fabric defects,” International Journal of Advanced Research, vol. 4, no. 8, pp. 1137–1141, 2016.

[9] L. Song, R. Li, and S. Chen, “Fabric defect detection based on membership degree of regions,” IEEE Access, vol. 99, p. 1, 2020.

[10] P. M. Mahajan, S. R. Kolhe, and P. M. Patil, “A review of automatic fabric defect detection techniques,” Advances in Computational Research, vol. 1, no. 2, pp. 18–29, 2009.

[11] H. Y. T. Ngan, G. K. H. Pang, and N. H. C. Yung, “Automated fabric defect detection-A review,” Image and Vision Computing, vol. 29, no. 7, pp. 442–458, 2011.

[12] M. T. Habib, S. B. Shuvo, M. S. Uddin et al., “Automated textile defect classification by bayesian classifier based on statistical features,” in Proceedings of the 2016

International Workshop on Computational Intelligence (IWCI), Dhaka, Bangladesh, December 2016.

[13] J. L. Raheja, S. Kumar, and A. Chaudhary, "Fabric defect detection based on GLCM and Gabor filter: a comparison," Optik, vol. 124, no. 23, pp. 6469–6474, 2013.

[14] J. L. Raheja, B. Ajay, and A. Chaudhary, "Real time fabric defect detection system on an embedded DSP platform," Optik, vol. 124, no. 21, pp. 5280–5284, 2013.

[15] R. S. Sabeenian, "Fabric defect detection using discrete curvelet transform," Procedia Computer Science, vol. 133, pp. 1056–1065, 2018.

[16] P. Senthil Kumar and H. Hafedh, "Detection of defects in knitted fabric images using Eigen values," International Journal Computer Science Engineering-IJASCSE, vol. 2, no. 3, pp. 7–10, 2013.

[17] L. Song, R. Li, and S. Chen, "Fabric defect detection based on membership degree of regions," IEEE Access, vol. 99, p. 1, 2020.

[18] M. B. Gharsallah and E. B. Braiek, "A visual attention system based anisotropic diffusion method for an effective textile defect detection," Journal of the Textile Institute, vol. 8, pp. 1–15, 2020.

[19] M. S. Sayed, "Robust fabric defect detection algorithm using entropy filtering and minimum error thresholding," in Proceedings of the 2016 IEEE 59th International Midwest Symposium on Circuits and Systems (MWSCAS), Abu Dhabi, UAE, October 2016.

[20] R. M. L. N. Kumari, "Sylvester matrix based similarity estimation method for automation of defect detection in textile fabrics," Journal of Sensors, vol. 2021, Article ID 6625421, 11 pages, 2021.

[21] D. Chetverikov and A. Hanbury, "Finding defects in texture using regularity and local orientation," Pattern Recognition, vol. 35, no. 10, pp. 2165–2180, 2002.

[22] L. Chen, S. Zeng, Q. Gao et al., "Adaptive gabor filtering for fabric defect inspection," Journal of Compurters, vol. 31, no. 2, pp. 45–55, 2020.

[23] J. Zhang, Y. Li, and H. Luo, "Defect detection in textile fabrics with optimal Gabor filter and BRDPSO algorithm," Journal of Physics: Conference Series, vol. 1651, p. 012073, 2020.

[24] B. A. TanveerSajid, "Fabric defect detection in textile images using gabor filter," IOSR Journal of Electrical and Electronics Engineering, vol. 3, no. 2, 2012.

[25] H. C. Sulochan, “Fabric weave pattern detection based on fuzzy clustering and texture orientation features in wavelet domain,” Journal of Textile Science & Engineering, vol. 8, no. 6, 2018.

[26] N. Vermaak, P. Nsengiyumva, and N. Luwes, “Using the dual-tree complex wavelet transform for improved fabric defect detection,” Journal of Sensors, vol. 2016, Article ID 9794723, 8 pages, 2016.

[27] G. Liu and X. Zheng, “Fabric defect detection based on information entropy and frequency domain saliency,” Visual Computer, vol. 24, 2020.

[28] L. Di, H. Long, and J. Liang, “Fabric defect detection based on illumination correction and visual salient features,” Sensors, vol. 20, no. 18, 2020.

[29] J.-F. Jing, S. Chen, and P.-F. Li, “Fabric defect detection based on golden image subtraction,” Coloration Technology, vol. 133, 2017.

[30] I. S. Mohammed and I. M. Alhamdani, “A fuzzy system for detection and classification of textile defects to ensure the quality of fabric production,” International Journal of Electrical and Computer Engineering, vol. 9, no. 5, 2019.

[31] D. Yapi, M. S. Allili, and N. Baaziz, “Automatic fabric defect detection using learning-based local textural distributions in the contourlet domain,” IEEE Transactions on Automation Science and Engineering, vol. 15, no. 3, pp. 1014–1026, 2018.

[32] P. Li, H. Zhang, J. Jing, R. Li, and J. Zhao, “Fabric defect detection based on multi-scale wavelet transform and Gaussian mixture model method,”

[33] A. Rebhi, I. Benmhammed, S. Abid, and F. Fnaiech, “Fabric defect detection using local homogeneity analysis and neural network,” Journal of Photonics, vol. 2015, Article ID 376163, 9 pages, 2015.

[34] H. Y. T. Ngan, G. K. H. Pang, S. P. Yung, and M. K. Ng, “Wavelet based methods on patterned fabric defect detection,” Pattern Recognition, vol. 38, no. 4, pp. 559–576, 2005.

[35] L. Jia and J. Liang, “Fabric defect inspection based on isotropic lattice segmentation,” Journal of the Franklin Institute, vol. 354, no. 13, pp. 5694–5738, 2017.

[36] L. Jia, J. Zhang, S. Chen, and Z. Hou, “Fabric defect inspection based on lattice segmentation and lattice templates,” Journal of the Franklin Institute, vol. 355, no. 15, pp. 7764– 7798, 2018.

[37] L. Jia, C. Chen, S. Xu, and J. Shen, “Fabric defect inspection based on lattice segmentation and template statistics,” Information Sciences, vol. 512, pp. 964–984, 2020.

[38] X. Chang, C. Gu, J. Liang et al., “Fabric defect detection based on pattern template correction,” Mathematical Problems in Engineering, vol. 2018, Article ID 3709821, 17 pages, 2018.

[39] B. Shi, J. Liang, L. Di, C. Chen, and Z. Hou, “Fabric defect detection via low-rank decomposition with gradient information and structured graph algorithm,” Information Sciences, vol. 546, pp. 608–626, 2021.

[40] A. Abouelela, H. M. Abbas, H. Eldeeb, A. A. Wahdan, and S. M. Nassar, “Automated vision system for localizing structural defects in textile fabrics,” Pattern Recognition Letters, vol. 26, no. 10, pp. 1435–1443, 2005. [41] H. Y. T. Ngan, G. K. H. Pang, and N. H. C. Yung, “Motifbased defect detection for patterned fabric,” Pattern Recognition, vol. 41, no. 6, pp. 1878–1894, 2008.

[41] H. Y. T. Ngan, G. K. H. Pang, and N. H. C. Yung, “Ellipsoidal decision regions for motif-based patterned fabric defect detection,” Pattern Recognition, vol. 43, no. 6, pp. 2132–2144, 2010.

[42] L. Bissi, G. Baruffa, P. Placidi, E. Ricci, A. Scorzoni, and P. Valigi, “Automated defect detection in uniform and structured fabrics using Gabor filters and PCA,” Journal of Visual Communication and Image Representation, vol. 24, no. 7, pp. 838–845, 2013.

[43] Y. Shu, L. Zhang, D. Zuo et al., “Analysis of texture enhancement methods for the detection of eco-friendly textile fabric defects,” Journal of Intelligent & Fuzzy Systems, pp. 1–11, 2021.

[44] H.-G. Bu, J. Wang, and X.-B. Huang, “Fabric defect detection based on multiple fractal features and support vector data description,” Engineering Applications of Artificial Intelligence, vol. 22, no. 2, pp. 224–235, 2009.

[45] H.-G. Bu, X.-B. Huang, J. Wang, and X. Chen, “Detection of fabric defects by auto-regressive spectral analysis and support vector data description,” Textile Research Journal, vol. 80, no. 7, pp. 579–589, 2010.

[46] B. Shi, J. Liang, L. Di et al., “Fabric Defect Detection via LowRank Decomposition With Gradient Information,” IEEE Access, vol. 99, p. 1, 2019

[47] Lettry, L.; Perdoch, M.; Vanhoey, K.; Gool, L.V. Repeated Pattern Detection Using CNN Activations. In Proceedings of the IEEE Winter Conference on Applications of Computer Vision, Santa Rosa, CA, USA, 27–29 March 2017; pp. 47–55.

[48] Chen, L.-C.; Zhu, Y.; Papandreou, G.; Schroff, F.; Adam, H. Encoder-decoder with atrous separable convolution for semantic image segmentation. In Proceedings of the European Conference on Computer Vision, Munich, Germany, 8–14 September 2018; pp. 801–818.

[49] Han, K.; Wang, Y.; Tian, Q.; Guo, J.; Xu, C. GhostNet: More Features from Cheap Operations. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 13–19 June 2020; pp. 1580–1589.

[50] Zucker, S.W.; Terzopoulos, D. Finding structure in co-occurrence matrices for texture analysis. Comput. Graph. Image Process. 1980, 12, 286–308. [CrossRef]

[51] Unser, M. Sum and Difference Histograms for Texture Classification. IEEE Trans. Pattern Anal. 1986, 8, 118. [CrossRef]

[52] Liu, Y.; Collins, R.T.; Tsin, Y. A Computational Model for Periodic Pattern Perception Based on Frieze and Wallpaper Groups. IEEE Trans. Pattern Anal. 2004, 26, 354–371.

[53] Nasri, A.; Benslimane, R.; Ouaazizi, A.E. A Genetic Based Algorithm for Automatic Motif Detection of Periodic Patterns. In Proceedings of the IEEE Tenth International Conference on Signal-Image Technology & Internet-Based Systems, Marrakech, Morocco, 23–27 November 2014; pp. 112–118.

[54] Xiang, Z.; Zhou, D.; Qian, M.; Ma, M.; Hu, X. Repeat pattern segmentation of print fabric based on adaptive template matching. J. Eng. Fibers Fabr. 2020, 15, 155892502097328. [CrossRef]

[55] Mallik-Goswami, B.; Datta, A.K. Detecting defects in fabric with laser-based morphological image processing. Text. Res. J. 2000, 70, 758–762. [CrossRef]

[56] Tsai, D.M.; Huang, T.Y. Automated surface inspection for statistical textures. Image Vis. Comput. 2003, 2, 307–323. [CrossRef] 25. Cohen, F.S.; Fan, Z. Automated inspection of textile fabrics using textural models. IEEE Trans. Pattern Anal. 1991, 13, 803–808. [CrossRef]

[57] Zuo, H.; Wang, Y.; Yang, X.; Xin, W. Fabric Defect Detection Based on Texture Enhancement. In Proceedings of the 5th International Congress on Image and Signal Processing, Chongqing, China, 16–18 October 2012; pp. 876–880.

[58] Chen, L.C.; Papandreou, G.; Kokkinos, I.; Murphy, K.; Yuille, A.L. DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Trans. Pattern Anal. 2018, 40, 834–848. [CrossRef] [PubMed]

[59] Hu, J.; Shen, L.; Sun, G. Squeeze-and-Excitation Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–22 June 2018; pp. 7132–7141.

[60] Bochkovskiy, A.; Wang, C.-Y.; Liao, H.-Y.M. Yolov4: Optimal speed and accuracy of object detection. arXiv 2020, arXiv:2004.10934.

[61] Ren, R.; Hung, T.; Tan, K.C. A Generic Deep-Learning-Based Approach for Automated Surface Inspection. IEEE Trans. Cybern. 2018, 43, 929–940. [CrossRef] [PubMed]

[62] Li, Y.; Zhang, D.; Lee, D.J. Automatic fabric defect detection with a wide-and-compact network. Neurocomputing 2019, 329, 329–338. [CrossRef]

[63] Jing, J.; Wang, Z.; Rätsch, M.; Zhang, H. Mobile-Unet: An efficient convolutional neural network for fabric defect detection. Text. Res. J. 2022, 92, 30–42. [CrossRef]

[64] Hu, G.; Huang, J.; Wang, Q.; Li, J.; Xu, Z.; Huang, X. Unsupervised fabric defect detection based on a deep convolutional generative adversarial network. Text. Res. J. 2020, 90, 247–270. [CrossRef]

[65] Mei, S.; Wang, Y.; Wen, G. Automatic Fabric Defect Detection with a Multi-Scale Convolutional Denoising Autoencoder Network Model. Sensors 2018, 18, 1064. [CrossRef]

[66] Hu, X.; Fu, M.; Zhu, Z.; Xiang, Z.; Qian, M.; Wang, J. Unsupervised defect detection algorithm for printed fabrics using content-based image retrieval techniques. Text. Res. J. 2021, 91, 2551–2566. [CrossRef]

[67] Krizhevsky, A.; Sutskever, I.; Hinton, G. ImageNet Classification with Deep Convolutional Neural Networks. In Proceedings of the Advances in Neural Information Processing Systems, Lake Tahoe, NV, USA, 3–6 December 2012; pp. 1097–1105.

[68] Sifre, L. Rigid-Motion Scattering for Image Classifiification. Ph.D. Thesis, Ecole Polytechnique, CMAP, Paris, France, 2014.

[69] Howard, A.; Sandler, M.; Chu, G.; Chen, L.-C.; Chen, B.; Tan, M.; Wang, W.; Zhu, Y.; Pang, R.; Vasudevan, V. Searching for mobilenetv3. In Proceedings of the IEEE/CVF International Conference on Computer Vision, Seoul, Korea, 27 October–3 November 2019; pp. 1314–1324.

[70] Lin, T.Y.; Goyal, P.; Girshick, R.; He, K.; Dollár, P. Focal Loss for Dense Object Detection. IEEE Trans. Pattern Anal. 2018, 42, 318–327. [CrossRef]

[71] Paszke, A.; Gross, S.; Chintala, S.; Chanan, G.; Yang, E.; Devito, Z.; Lin, Z.; Desmaison, A.; Antiga, L.; Lerer, A. Automatic Differentiation in PyTorch. In Proceedings of the NIPS 2017, Long Beach, CA, USA, 4–9 December 2017.

[72] Bottou, L. Large-Scale Machine Learning with Stochastic Gradient Descent. In COMPSTAT02010, Proceedings of the 19th International Conference on Computational Statistics, Paris, France, 22–27 August 2010; Springer: Heidelberg, Germany, 2010; pp. 177–186.

[73] Tsang, C.S.; Ngan, H.Y.; Pang, G.K. Fabric inspection based on the Elo rating method. Pattern Recogn. 2016, 51, 378–394. [CrossRef]

[74] Workgroup on Texture Analysis of DFG's. TILDA Textile Texture Database. Available online: https://lmb.informatik.unifreiburg.de/resources/datasets/tilda.en.html (accessed on 10 July 2022).

[75] Shelhamer, E.; Long, J.; Darrell, T. Fully Convolutional Networks for Semantic Segmentation. IEEE Trans. Pattern Anal. 2017, 39, 640–651. [CrossRef] [PubMed]

[76] Ronneberger, O.; Fischer, P.; Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention, Munich, Germany, 5–9 October 2015; pp. 234–241.

[77] Ali, R.; Chuah, J.H.; Talip, M.S.A.; Mokhtar, N.; Shoaib, M.A. Automatic pixel-level crack segmentation in images using fully convolutional neural network based on residual blocks and pixel local weights. Eng. Appl. Artif. Intell. 2021, 104, 104391. [CrossRef]

[78] Pratt, L.; Govender, D.; Klein, R. Defect detection and quantification in electroluminescence images of solar PV modules using U-net semantic segmentation. Renew. Energy 2021, 178, 1211–1222. [CrossRef]

[79] Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A.; Chen, L.C. MobileNetV2: Inverted Residuals and Linear Bottlenecks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–22 June 2018; pp. 4510–4520.