Fabric Defect Detection using Computer Vision

# Summary

This report aims to how computer vision could be used to find defect in narrow fabric. Utilising the open source technologies, OpenCV and TensorFlow to create 3 different inspection techniques and Qt to build a fabric inspection GUI.

\*\*\* pre-processing maybe \*\*\*

The three inspection techniques were all created in python using OpenCV. The first used created and examined histograms generated form the pixel values of the images. The second utilised image morphology and contour finding to look for large objects present in the image. The last method leveraged TensorFlow to build a CNN (Convolutional Neural Network) that was trained on pre labelled defect data obtained from the aitex fabric image database.

A prototype graphical application was then created using the second and third inspection techniques and the report discusses how this would be implemented in a full inspection system. Finally, the report compares the inspection techniques created to human inspection, the current method most companies use. \*\* explain findings \*\*

The report concluded \*\* conclusion \*\*

# Acknowledgements

I would like to thank my assessor \*\*name\*\* and both of my supervisors Amy Lowe and David Head who provided indispensable guidance throughout the project.

I would also like to thank my friends who provided much needed data around human inspection.

Finally I would like dedicate this report to my late father Charles, who inspired the idea for the project. \*\* add more about dad \*\*

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# Chapter 1: Introduction and Background Research

## Introduction

The purpose of this project was to explore how computer vision could be used in fabric defect detection and what advantages it could offer over traditional methods.

This project and report will investigate the effectiveness of different computer vision techniques at locating defects in images of fabrics. To carry out this investigation three different inspection techniques were created, the first two using OpenCV and the last using TensorFlow.

Lastly, a prototype application was created that would be used to automatically inspect a user supplied images using the most effective inspection methods found in the initial stages of the project.

## Fabric

Most fabric / textile is produced through one of a number of processes weaving, knitting, felting, bonding or turfing. Out of these the most common are weaving and knitting which produces most conventional fabrics. Both involve very similar steps, first fibres (synthetic or natural) are spun into yarn which is then converted into fabric using either weaving or knitting (Shaker,2016).

As these two production methods are the most widespread the projects definition of a fabric or textile was limited to those produced by either of these two methods. To understand the problem and what defects can occur, it was important to have a surface level understand of how these production technique’s function.

### Spinning

First fibres are harvested naturally for example flax or are produced synthetically such as polyester. These are then aligned and collected into yarn through the process of spinning, this process varies for natural and synthetic material. Natural fibres can be spun in many ways, but all involve them being twisted, this binds them together to form yarn (Smith, 1969, p. 1).

Synthetic fibres are spun differently, here liquid polymer is extruded though many, densely packed small holes. A cool “quench air” is passed over them to solidify the liquid polymer into long continuous fibres. Variations in the air passed over them also causes fibres to bunch in certain areas binging them together into yarn (Denn, 1983, pp. 179-180).

### Weaving and Knitting

After yarn is created, weaving and knitting are two processes that can be used to convert this yarn into fabric. Weaving is the process of interlacing yarn perpendicularly to each other. The patterns this is done in determine the properties and appearance of the textile (Adanur, 2020, p. 1). Terms used later in the project are warp and weft and they are key when understanding the weaving process. All woven fabric consists of warp and weft yarns, warp yarns are the yarns that run parallel to the edge / selvage of the fabric and are used to form its structure. Weft yarns are those running perpendicular to the edge of the fabric and are interlaced between the warp yarns using a loom (Lord,1982).

Knitting is the second most prevalent for of textile manufacturing. It is achieved by vertically intermeshing loops of yarn (Ray, 2012, p.2). Similarly, to weaving the way in which the loops mesh decides the properties and appearance of the final textile. While they processes differ Both methods aim to produce an ordered and reoccurring structure of yarn.

### Dyeing

Once these textiles are produced most if not all go through some level of processing. This may include dyeing a form of post processing that colours the fabric with a dye or pigment. There are many ways to dye a fabric but the common is the batch dyeing processes. The batch dyeing processes involves a textile being submerged in a large quantity of dye for an extended period, this allows the dye to transfer into the textile (Perkins, 1991, p. 23).

Many other finishing processes can also be applied such as coatings, but these are less prone to producing visible defects and so do merit discussion.

## AITEX Fabric Image Database

This project developed using the AITEX fabric image database( <https://www.aitex.es/afid/> ) and its accompanying article “A PUBLIC FABRIC DATABASE FOR DEFECT DETECTION METHODS AND RESULTS” (Silvestre-Blanes, 2019, pp.363-374). The article explains how the database was created and explores some detection methods. The database consists of 245 images ranging over 7 different types of woven fabric. It contains 140 images of defect free fabric, 20 each type of fabric. With 105 images of defective fabric spread between all 7 fabric and 12 defect types.

Usefully the database also contains 105 mask images for each image of defective fabric, theses mask images match the dimensions of the fabric images (4096×256 pixels). The masks contain only black pixels apart from the pixels that make up the defect, these are coloured white.

### Types of Defects

Now the project has a baseline understanding of how fabric is created and a database to refence from we can assess what defects are produced during the phases of its creation.

The twelve defect types present in the AITEX database are:

* Fuzzy balls. Fuzzy balls are the result of warp yarns that are too small lowering their abrasion resistance allowing fibres to break loose and form fuzz balls. According to cotton works list of defects.
* Neps. Neps are formed by an accumulation of fly and fluff on the machinery used and result in damage the fabrics appearance when dyeing (Nateri, 2014). Often caused in the spinning process.
* Knots. Knots occur in natural or synthetic warp yarns and damage the appearance and tensile strength of the textile. Knots can also refer dead or immature natural fibres (Lim, 2018).
* Crease. A crease is a valley or ridge present in the final fabric caused by folding or improper tension.
* Broken End. A broken end appears as an untied or broken warp end and manifests as horizontal lines in the lines in the fabric. The yarn is usually broken during weaving or finishing processes (Lim, 2018).
* Broken pick. A broken pick defect consists of a broken weft yarn and results in a sudden discontinuity in the weave (Lim, 2018).
* Broken yarn. Broken yarns are breaks in either the warp or weft yarn during the weaving process and result in elongated holes.
* Contamination. Contamination refers foreign objects suck too or woven into the textile. Even if the object is later removed it may have disturbed the weave or cause uneven dyeing.
* Warp ball. A warp ball is caused by a single or multiple warp yarns becoming clumped or entangled.
* Cut selvage. Selvage a is the densely woven edge of a piece of fabric a cut in the selvage can cause a separation in the weave (Lim, 2018).
* Weft Curling. Weft curling Is produced by the use of highly twisted weft yarn as a result it disturbs the pattern of the weave. According to Textile Tutorials.
* Weft Crack. A weft crack results in a narrow streak running in parallel with the weft caused by an absence of weft yarn. According to Textile Sphere.

Calendar

Description automatically generated with low confidenceFigure 1. ROI of 256 x 256 pixels from original images of defective fabrics, with the names used in the database. (a) broken end, (b) broken yarn, (c) broken pick, (d) weft curling, (e) fuzzy ball, (f) cut selvage, (g) crease, (h) warp ball, (i) knot, (j) contamination, (k) nep, and (l) weft craft. ROI, region of interest (Silvestre-Blanes, 2019).

Figure - Defect Images (Silvestre-Blanes, 2019)

### Importance of Inspection

Fabric inspection is important for a multitude of reasons, the upmost being the prevention of inferior quality product being sold to or used by consumers (Malek, 2013). Inferior or defective product being used or sold can cause a variety consequence for the producer.

Inspection at early stages, straight after weaving, can finically be benefit the producer it stops the offending sections being processed further or being sold to those who will apply finishing processes. Supplying defective fabric is likely to cause animosity directed towards the fabric supplier, worsening customer satisfaction and possibly affecting future revenue.

The garment industry represents one largest purchasers of textiles, they need assurance the raw materials they purchase are defect free. Many of the designer brands will expect or enforce that textiles be inspected before purchase and are unafraid to hold producers accountable, as their clientele expect a level of quality.

Defects are not only cosmetically undesirable many effect the structure of the weave and so can degrade its tensile strength. Ultimately leading to textiles being distributed with a lower tensile strength than advertised, creating the potential for catastrophic failures. For example, it is key that seat belts or ratchet straps have no structural defects.

## Current Inspection Techniques

Currently fabric inspection techniques vary, the majority use human inspection. Human inspection uses workers to scrutinise fabric by hand. The accuracy of human inspection declines over time due monotonous nature of the task. This results in slower, more expensive, and erratic inspection (Chin, 1982).

Many in the industry paired a use of human inspection with inspection using DSP (digital signal processing). DSP would analyse the waveform produced by a sensor pointed at the fabric in controlled lighting. However, most are now moving towards computer vision approaches as they easier to implement and are more capable at inspecting a variety if fabrics.

## Computer Vision

Computer vision is defined as the processes of allowing computers to see the real world (Learned-Miller, 2011), it encompasses capturing, processing and analysing images. Computer vision has proven invaluable when automating quality control. It offers higher accuracy and speed than human inspection but more importantly it is far more consistent, not suffering from the inconsistent results as the day progresses (Brosnan, 2004).

There are a number of code libraries that enable computer vision, Google, Microsoft and Amazon all have offerings. However, the most widely used computer vision library is OpenCV created by intel and free to use in any application. It offers a wide range of functions allowing the capture and processing of images.

Image morphology encompasses a broad set of image processing operations based on the boundaries of shapes. The most common forms are erosion, dilation, opening and closing (Haralick,1987). Erosion reduces the size of objects, particularly important when reducing noise in an image. As images of fabric are inherently noisy due to the repeating weave, image morphology may be key when emphasising larger objects and defects in an image. OpenCV offers all of these morphological transformations in optimised functions, however each can only be applied to a greyscale image.

Conversion to greyscale, thresholding and contour tracking functions are all offered by OpenCV. Converting and image to greyscale replaces each 3-channel pixel composed of a red, green, and blue value to a single grey value. Greyscale images are easier to process and are required for many other image processing algorithms. Thresholding converts a greyscale image into a bi-level image and is usually used to separate foreground objects from a background. Contour finding can be used to find the boundary of an object (Xie, 2013), all will be useful in the project. Guobo Xie and Wen Lu used all the above methods to detect the number of copper strands in a small wire, checking to see if the correct number was present. A number of deep learning libraries offer premade CNN’s such as VGG 16 offered by keras.

## Computer Vision Quality Control

The paper ‘AUTOMATIC IMAGE PROCESSING ENGINE ORIENTED ON QUALITY CONTROL OF ELECTRONIC BOARDS’ written by Alessandro Massaro, Valeria Vitti and Angelo Galiano. Details how computer vision is was used to find defects on electronic boards after welding and how the final method was calibrated and tested.

The paper details a number of steps involved in these processes. The first was to segment the image, this involves splitting the image into a number of small groups of pixels, simplifying the image and making easier to analyse, the snake contour and watershed are two processes used to segment. They then applied thresholding to separate the welds from the background of the boards, the area of the resulting blobs used to identify any that were defective. While the report did not detail exactly how effective these techniques they offer insight into processes that could be used in this project (Massaro, 2018).

## Machine learning

The term machine learning describes a set of methods or algorithm that make predictions based on previous data they have been shown (Zhou, 2021). This project will focus on an area of machine learning named deep learning. All deep learning techniques use multiple layers to find or extract feature from data. There are a number of methods that can be used when classifying images, recurrent neural networks (RNN), long short-term memory (LSTM) and artificial neural networks (ANN) are some of these but the most popular is the convolutional neural network (CNN). They gained this popularity as they work particularly well at image /classification, image recognition and object detection tasks and so were there clear choice when developing the project.

CNN’s processes an image through multiple layers, some of these acts as filters that are trained to recognise different features in the image such as corners, edges and patterns. These filtering layers are knows as convolutional layers, two other type of layers are also present in CNN’s these being max pooling and fully connected layers. Each convolutional layer is comprised of a number of filters, these filters are simply a matrix of weights with smaller dimensions that the input image, during training these weights are adjusted. The output of the convolutional / convolution layer are passed through an activation function such as ReLU to a max pooling layer, the max pooling layer reduces the outputs size while preserving the most important features. This helps in two ways; it reduces the computational complexity of the model speeding up the time it takes to predict and offers some protection against overfitting. The last step of CNN id the fully connected layer this takes an output of a previous layer scaling it down and producing a set of scores that each relate to a specific class using a final activation function (O'Shea, 2015). This is only a brief overview of how a CNN functions.

## Background research summary

Automated systems can hold a clear advantage over manual inspection methods in both speed and accuracy, however there are many challenges. As shown above in figure 1 defects can vary in the size, colour and shape while this does not impact manual human inspection it makes rule based automated inspection far more complicated. There also exist the issue of when to inspect as many defects are unique to a specific step of production. Hence the project will move forward with the assumption that all inspection will be done after any finishing processes. While this is not optimum as inspection would be easier and more money and time could be saved if inspection occurred in earlier stages. However, for the sake of creating a universal inspection system inspection must occur on the finished fabric as each producers’ methods are likely to differ.

Researching methods previously used for quality control and image processing have informed how the project will develop. The use of OpenCV using morphology and contour tracking have been successful when identifying defects in products. However, the previously discussed study ‘AUTOMATIC IMAGE PROCESSING ENGINE ORIENTED ON QUALITY CONTROL OF ELECTRONIC BOARDS’ classified defects purely based on size. It is still unclear if an approach like this will work with fabric defects, as depicted in figure 1 defects differ from normal fabric in several categories not just size.

A CNN will likely be suited to this project due to its ability to recognise shape and texture. However it is unlikely that the AITEX consisting of 245 images will be enough to achieve a reasonable level of accuracy and so some from of image segmentation will be required.

# Chapter 2: Methods

The goal of this chapter is to address the design and implementation of the three inspection techniques mentioned earlier and create the prototype inspection application. All were completed in python utilising OpenCV, TensorFlow and PyQt5.

## Initial Project Decisions

This projected was developed using the agile methodology, using sprints to manage milestones. This method suited the project as in any form of inspection results and the timand es in which they are achieved are not guaranteed. This allowed some area of the project to always be in active development, even during long model training periods or when certain avenues of thought lead to dead ends.

Version controlled was used throughout and was facilitated with a GitLab repository. <https://gitlab.com/TomSchofield/personalproject>

The decision to use the aitex image fabric defect database informed what detection methods would be perused and how they would be evaluated. There was another choice, the University of Moratuwa fabric defect database (Belkhir, 2020). This included a far greater amount defect of data however it was split between only 5 defect types: colour, cut, hole, thread, metal contamination. All images from this dataset are also all from one type of fabric (figure 2). For these reasons and the fact the type of fabric is less widespread than that found in the aitex database, it was decided that while accuracy might suffer the inspection methods produced would be more general if the project used the aitex database.

Figure - Sample Fabric (Belkhir, 2020)

One of the initial ideas for the project was to include some form of defect categorisation, this would separative images already deemed as defective into individual categories. However once development commence it was decided that this was out of the scope of the project, the primary reason for this is the lack of large enough datasets. The dataset chosen contained at most 20 images of each defect type and so does contain enough data to train a defect categorisation algorithm and achieve a reasonable accuracy. Hence the decision to focuses efforts on defect detection.

## Sprint 1: Data Preparation and Analysis

### Goals and Design Decisions

The goals for the first sprint were to prepare and investigate the dataset.

Figure - image 0001\_002\_00



Figure 3 shows an example image form the dataset; all images are standardised to a size of 4096×256 pixels. This presents two main problems the first is that the pixels that make up the defect represent a very small proportion of the overall image. The second is that any operations on such a large image would take a substantial amount of time.

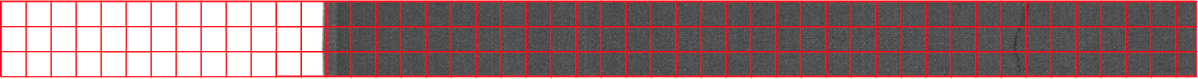


Figure - Tiled 0001\_002\_00

Figure 4 shows the solution to this issue, to segment the image. Once the image is segmented these tiles could be processed individually. furthermore, defective pixels represented a much larger proportion of the tile, they reside in.

However, when examining figure 4 a flaw in this methodology appears, we can see that approximately the first quarter of the image is the background behind the fabric. Hence the tiles in the section contain no meaning full information and would probably be miss classified as detective. To remedy this the background must be removed.

The last goal will be to store the created tiles as either a defective or normal. However this presents some issues as not all tiles from a defective image are themselves defective, the mask images from the database will likely be useful here.

### Implementation

All code development in this sprint was done in the ‘img\_crop.ipynb’ and ‘tile\_gen.ipynb’ files found in the repository.

#### Tile Class

Once the data was downloaded to implement the tiling routing was done by creating a class to represent the tile.

class Tile:

    x = 0

    y = 0

    width = 0

    height = 0

    imagex = 0

    imagey = 0

    roi = None

    overlap = 0

Code Snippet 1 – Tile Class Attributes

This Tile class holds all the key attributes needed when describing the contents and location of the segment in relation to the master image. The attributes “x” and “y” hold the position of the tiles in relation to the other tiles. Whereas “imagex” and “imagey” hold the position of the tile in relation to the pixels of the master image. For example a the second tile on the second row would have “x” and “y” value of 1. However, assuming a tile “width” and “height” of 64 and a “overlap” of 0 the same tile would have the value of 64 for both the “imagex” and “imagey”. Overlap simply describes the amount the tiles overlap and is calculated from the right most corner of the previous tile. Figure 5 shows of overlap is visualised.

A picture containing rectangle

Description automatically generated

Figure - Overlap Visualisation

    def populate(self,master):

        self.roi = master[y:y+height, x:x+width]

        if (self.roi.shape[1] < width):

            new\_x = x - (width-self.roi.shape[1])

            self.roi = master[y:y+height, new\_x:new\_x+width]

            self.imagex = new\_x

        if (self.roi.shape[0] <height):

            new\_y = y - (height-self.roi.shape[0])

            self.roi = master[new\_y:new\_y+height, x:x+width]

            self.imagey = new\_y

Code Snippet 2 – population method

Code snippet 2 shows the implementation of the populate method of the tile class. It takes the master image as a parameter and calculates which segment of the image should be copied into the tile’s “roi” (region of interest). The rest of the snippet relaxes the overlap constraint if the tile is not the correct size. This happens at the edge of the master image where there aren’t enough pixels to fill an entire tile.

### Tiling the image

\*\*insert code if space\*\*

Tiling the image is quite simple and is done inside the “tileImage()” function. First the number of tiles that should be created is calculated this is done by finding the number of tiles in bot the x and y axis. The number of tiles in the x direction is found by rounding up to the nearest integer the width of the image divided by the width of the tile minus the overlap. The same can be done to find the number of tiles along the y axis using the image height and tile height.

The number of tiles in either direction is the looped over and each tile is created and populated, the x and y coordinates if the tile in relation to the pixels in the master image is calculated by multiplying the x and y coordinates in relation to the other tiles times the height or width of the tile minus the overlap. These were then placed into a 2d array so they can be easily accessed.

### Preparing the images

As described in the goals of this sprint the images needed to be cropped to remove the background. Unfortunately, the exact location of the edge of the fabric was not in the same location for each image. First the images needed to be loaded in from the memory to do the OpenCV function “imread()” when supplied with a file path loads the image into a NumPy array. A NumPy array functions very similarly to a C or C++ array, they are fast accesses and have strict requirements on the homogeneity of the objects. However, they do allow some functionality of a python list such as the ability to append to them.

A picture containing timeline

Description automatically generatedOnce the image was loaded in the subroutine “findEdge()” was created. “findEdge()” takes an image in as a parameter and applies three processes to determine its edge first a light blur is applied to the image, then a threshold is applied and finally Canny edge detection is used to find all vertical edges present in the image.

Figure - Edge Finding Steps

Figure 6 demonstrates the steps involved when finding the edge of the fabric. (b) displays the conversion of the image to greyscale, this is needed to apply thresholding. Conversion to greyscale is simple achieved using a build in OpenCV function, it changes the given image from three channel colour (blue, green, red) to a single channel. This single channel ranges from 0 (black) to 255 (white). Blurring was also achieved using the OpenCV function “blur()”, this function receives the image to be blurred and the size of the kernel that should be used to blur and uses the widely know box blur algorithm. Box blur was used as it is substantially faster than other methods such as the Gaussian blur. The projected used a kernel of size 3 by 3, meaning each pixel was replaced by the average of the eight pixels surrounding and itself (Szeliski, 2022). The purpose of this blur is to reduce is to reduce noise or in this chase obscure the weave of the textile. This is needed as light spots can confuse the thresholding algorithm and vertical lines in the weave can confuse the canny algorithm.

(c) displays the output of the thresholding algorithm, once again this functionality is offered by an OpenCV function. The “threshold()” function again takes the parameters: the greyscale image to be processed, the threshold value, a maximum value and a tag representing the type of thresholding to be applied. The project uses binary inverse thresholding, any pixel in the image greater than the thresh hold value is set to 0 and any value less than the threshold value is set to the maximum value. The maximum value used in the project was 255 but any value would have been suitable and a threshold value of 240 as while the pixel values of the background were 255 some leeway should be left for inconsistency in the lighting of the images. The purpose of applying a threshold is to remove any vertical lines form the weave of the fabric leaving only the line between the background and fabric, removing any noise that may confuse the canny edge detection algorithm.

(d) the Canny edge detection algorithm again is offer by an OpenCV function. Canny edge detection works in stages, it first smooths the image to remove noise then computes the edge strength and edge direction. In simpler terms the edge strength and direction are found though the gradient of the image, a transition from black to white or vice versa is considered a positive or negative gradient. Edges usually produce a high magnitude gradient and so can be recognised as an edge (Xu, 2017). The OpenCV function uses further processing to clean up the edge. The “Canny()” function returns a list of pixels that constitute the edge, the innermost pixels location is then used to crop the image lengthwise. (c) The dimensions of the cropped images were then found using the “.shape” attribute of a NumPy array and the corresponding mask image was cropped to the same dimensions (f).

### Saving and labelling tiles

Now the images had been cropped the individual tile needed to be labelled and saved. Labelling is the processes of designating a class to each data item, in the context of this project this would be designating as either a defective or normal. As each image is broken down into approximately 540 individual tiles and the database consists of 245 images hand labelling would be infeasible. However, the cropped mask images can be used to determine which tiles include defects. All the mask images consist of only black and white pixels, the black pixels substitute any pixel in the original image that is not part of the defect. White pixels take the place of the pixels that do make up the defect.

As the mask were cropped along with the original images when segmented the tiles of both match. Figure 7 shows this relation.

Chart

Description automatically generated

Figure - Mask and Tile

Hence, if any mask tile contains any white pixels, its corresponding unmasked tile could safely be labelled as defective and those containing no white pixels as normal. In practice this method had one problem even those masks which contained only a single white pixel would be treated as defective, this is far too strict and could confuse later inspection methods. To remedy this only mask tiles that contained over 500 white pixels would be treated as defective.

This increased the number amount of data available from 245 large images to 909 defective tiles and 113,307 normal tiles at a more manageable size. This segmentation will allow for more detailed testing and training of inspection methods in later sprints.

### Sprint Review

At the end of this sprint all goals were achieved. There now existed functions that can successfully read images form the database, crop them, tile them, and save the tiled for later use.

During this sprint no detection methods were produced however all pre-processing was now complete making development of more detection methods faster.

## Sprint 2: Beginning Inspection

### Goals and Design Decisions

The goal of this sprit was to develop an analytical approach to inspection by comparing the properties of tiles to a known good tile.

The main goal for this sprint was to develop an inspection technique using the principle of object detection. To achieve this, a way to reduce noise in the image must be developed as well to find groups of similarly coloured pixels.

### Implementation

All code development in this sprint was done in the ‘detection\_methods.ipynb’ file found in the repository.

### Statistical Analysis

#### Histogram Generation

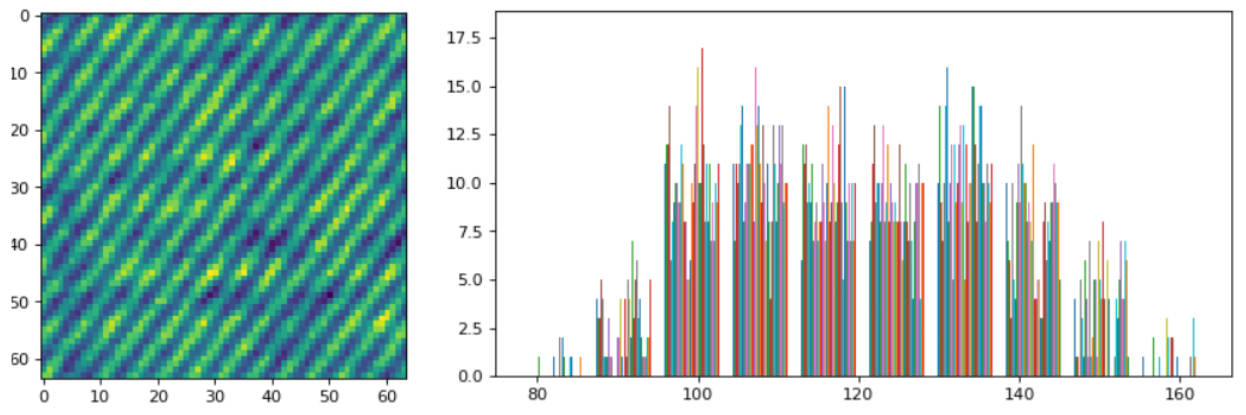
The first form of defect detection attempted was to analyse the pixel values of each tile of the image and compare them to a know good tile. A histogram of the pixel values from a greyscale conversion of the tile was created using the matplotlib “hist()” function.

Figure - Histogram of Non-Defective Tile

Figure 8 shows the histogram of a non-defective tile.

The idea was that some defective tiles differ in key metrics such as mean pixel colour or the range of the pixel values from ideal tiles. These could be used to identify defective tiles.

#### Metric Analysis

Two forms of statistical analysis were attempted, the first was an attempted to use the range and standard deviation of the pixel values within a tile to deduce whether its defective. The tiles greyscale image data inside the tiles are stored as NumPy array and so the standard deviation can be simply found using a the NumPy function “np.std()”. Range was found using a “findRange()” function created during the project. The function loops through all the pixel in the array and stores both the lowest and highest values found. The lowest can then be subtracted from the highest to return the range.

#### Colour Space Reduction

The next approach attempted was to reduce the colour space of the image. The idea was to reduce the colour space to a set of intervals and count the number of instances inside each interval with the hope that defective tiles will have abnormally high pixel counts in certain intervals. This was achieved by rounding pixel values to the closest interval.

The “roundTile()” functions is supplied with the tile to be processed and the intervals the pixels should be rounded too. This then calls the “roundPixel()” function on each pixel un the tile, this takes the absolute difference between the pixel value and each interval and returns the interval that produced the lowest difference.

Polygon

Description automatically generated

Figure - Colour Space Reduction and Plot

Figure 10 displays an original tile (a) the result of the colour reduction processes (b) and the plot of pixel colour against the occurrences of pixels of that colour in the colour reduced tile. It illustrates that the majority of pixels have a value of either 100 or 120.

After further investigation it was decided that any tile that over 2000 occurrence of a specific pixel value could be labelled as defective. Any tile with less than 1250 occurrence of value 80, more than 1800 occurrence of value 100, more than 1000 occurrence of value or 120, or over 500 occurrences of any value over and including 140 could be labelled as defective. This was implemented by the ‘reduceInspect()’ function.

#### Blob and Line Detection

OpenCV has many functions designed to assist in object detection, many of these functions will help when looking for defects as most if not all present as a large mass similarly coloured pixel. First the “SimpleBlobDetector” class provided by OpenCV was used but after many attempts and many different permutations of the “SimpleBlobDetector” parameters it could not detect even the most obvious defects.

#### Morphology and Contour Finding Inspection

Contour finding algorithms first need an image with very little noise. However as stated previously in the project images of fabric are inherently noisy do to the weave of the fabric. To reduce the noise a number of steps can be taken.

def findDefect(img, threshHold, pixThresh, lightBlur, errode, blur):

    exitCode = 0 # an exit code of 0 means a blob has been detected

    greyMaster = cv2.cvtColor(img, cv2.COLOR\_BGR2GRAY) # grey blob defect

    # Light blur to reduce size of small shadows and highlights

    lightBlur = cv2.blur(greyMaster, (lightBlur,lightBlur))

    # adjusted = setLims(lightBlur, 0 ,110) # massively increases time to run

    ret, adjusted = cv2.threshold(lightBlur, pixThresh,pixThresh,cv2.THRESH\_TRUNC)

    kernel = np.ones((errode,errode),np.uint8) # forms the matrix used when eroding

    erosion = cv2.erode(adjusted,kernel,iterations = 1)

    # large blur to hide background weave and increase the size of defects

    greyBlur = cv2.blur(erosion, (blur,blur))

    #threshold on Gray image

    thresh = cv2.adaptiveThreshold(greyBlur,255,cv2.ADAPTIVE\_THRESH\_MEAN\_C, cv2.THRESH\_BINARY, 101, 3)

    # Apply morphology open then close

    kernel = cv2.getStructuringElement(cv2.MORPH\_ELLIPSE, (5,5))

    blob = cv2.morphologyEx(thresh, cv2.MORPH\_OPEN, kernel)

    kernel = cv2.getStructuringElement(cv2.MORPH\_ELLIPSE, (9,9))

    blob = cv2.morphologyEx(blob, cv2.MORPH\_CLOSE, kernel)

    # invert blob

    blob = (255 - blob)

    # Get contours

    cnts = cv2.findContours(blob, cv2.RETR\_EXTERNAL, cv2.CHAIN\_APPROX\_SIMPLE)

Code Snippet 3, first half of the “findDefcet()” function.

First a light blur is a applied using the “blur()” function shown in code snippet 3 to shrink highlights and shadows and obscure the weave. This blur is achieved in the same way as blurring in the first sprit was and the factor the image was blurred by is controlled by the “lightBlur” parameter.

Highlights and shadows produced by inconsistent lighting needed to be removed. This was done by the function “setLims()” this function is supplied with an image and a lower and upper bound. The image is then iterated through, and new image array is created each pixels is appended to the new image array. However, if any pixel has a lower value of than the lower bound supplied it is appended as the lower bound, if any pixel has a value higher than the upper bound it is appended as the upper bound. Once every pixel had been processed the new image array is returned. The maximum and pixel threshold are both determined by the parameter “pixThresh”.

While this implementation worked its sequential implementation proved too slow and instead OpenCV thresholding was used to remove highlights. The thresholding was done using the same “threshold()” function, using a max and threshold value of 110 and the “THRESH\_TRUNC” tag. This tag changes how the function functions, values lower than the threshold are kept and not set to 0.

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Description automatically generated

Figure - Morphology Examples (https://docs.opencv.org/4.x/d9/d61/tutorial\_py\_morphological\_ops.html)

The next step to reduce noise was to start using image morphology. Several morphological transformations were used starting with erosion. Figure 12 demonstrates how erosion effects an image, the erosion algorithm attacks the boundaries of an object and leads to small object being completely removed. It does this by moving a kernel (2d matrix) across the image the anchor pixel, usually the centre pixel, is replaced by the minimum pixel value inside the area described by the kernel. The size of the kernel decides the amount the of erosion that takes place. Dilation, also shown in figure 12, works in a very similar way however the anchor pixel is replaced by the maximum pixel value instead increasing the size of objects. A heavier blur is then applied to reduce or even eliminate any remaining background noise and increase the size of defects that were just shrunk by erosion.

Adaptive thresholding is then applied, this is very similar to the thresholding done previously in the project, but instead of using a global threshold value chucks of the image are processed individually, and a local threshold value is computed for each.

To forms of morphology are then applied consecutively Opening and Closing. Opening applies erosion followed by dilation this again reduces noise and then increases the size of the defect. Closing applies dilation followed by erosion and fills in any gaps inside the defect that have been created from previous operation.

OpenCV contour finding is then used outline or bound the shape of the defect or defects. It works by finding all points on the boundary of an object if these points then form a loop a contour is found. This works best when used on binary images, where the object is white, and the background is black. This is another reason why adaptive thresholding was applied and why the image is inverted after the morphological transformations.

The end of the function simply checks if the size of any of the contours found is over a given value and is so the tile is deemed defective and an “exitCode” of 0 is returned.

A picture containing text

Description automatically generatedHowever, the was on major problem with this implementation, lighter defects would not be found. The initial thresholding was needed to remove highlights but would also remove lighter defects. This was easily fixed by ruining “findDefect()” function twice each tile, inverting the tile after the first call transforming any light defects into darker defects which are more easily detected. This was implemented in the “twoPassInspection()” function.

Figure - Inspection Steps

Figure 13 displays the result of each stage of the inspection function, while some steps may seem unnecessary, they become more necessary in smaller or more complex defects.

### Sprint Review

This sprint was moderately successful many of the goal were achieved. There now existed a method to analytically compare the segments of an image using several pixel intervals. However, this method could not accurately determine whether an image included a defect.

This was expected, the progress was made on the more complex inspection technique using image morphology and contour finding proved more effective at determining defects. However, its accuracy could improved upon by tuning many of the internal parameters that control the factor of blurring or eroding. This tuning would need to be done in a later sprint.

## Sprint 3: Parameter Tuning and TensorFlow

### Goals and Design Decisions

For this sprint the goals were to tune the contour finding inspection technique to increase it accuracy and start development on an inspection technique leveraging deep learning. The tuning will be done by exhausting lists of parameters until the highest accuracy is found. While this technique will likely be slow it will find the exact combination of parameters needed to find the maximum accuracy the method is capable of.

For the third and last inspection techniques developed in the project it was decided that some form of neural network would be trained to categorise image segments / tile as either defective or normal. A convolution neural network was the exact method chose. Hence second goal for this sprint is to develop an appropriate layer structure for the CNN and then train it. The CNN would be trained on the tile / segments of an image as the defects represent a larger proportion of the image. It also would increase the number of each label in training set. This will likely increase the inference time however accuracy was the key metric in this project.

Keras was used to create this CNN. While pre-built CNN’s such as VGG 16 are available many are too deep for this application. While deeper neural nets have more capacity to learn and so in some applications can reach higher accuracy, they require more training data than I have available, they can take longer when training and inferring and are more prone to overfitting. As the goal of the project was to create an application that could inspect several textiles overfitting was actively avoided. Instead, a shallower network that is easier to train was chosen.

### Implementation

#### Parameter Tuning

To make sure the second inspection technique was as accurate as possible multiple sets of parameters were looped through. So that this optimising could be done in a reasonable amount of time it was split up in to two sets of nested for loops. The first set was consisted of two for loops that iterated over two lists [50,100,150,200,250,300] and [50,60,70,80,90,100,110,120,140]. The first list decides the minimum size of a defect and the second contains what pixel value should be used when thresholding. The upper and lower bounds of the list was found through manual testing.

The Second set of for loops consisted of three nested for loops. The first two iterated over values 1-10 and controlled the factor of the first blurring and erosion filters. The third iterated over values 1-20 and controlled the amount of the heavier blur.

For each set of parameters 1000 randomly selected normal tiles and all 900 defective tiles were put through the inspection function and the accuracy was calculated. The set of parameters that produced the highest accuracy was then saved for later use.

#### CNN

In keras a CNN is produced by defining a number of layers. First a sequential model object was created this instructs keras to processes in series through the layers.

model = Sequential([

  layers.Rescaling(1./255, input\_shape=(img\_height, img\_width, 3)),

  layers.Conv2D(32, (3,3), padding='same', activation='relu'),

  layers.MaxPooling2D(),

  layers.Conv2D(64, (3,3), padding='same', activation='relu'),

  layers.MaxPooling2D(),

  layers.Conv2D(64, (3,3), padding='same', activation='relu'),

  layers.MaxPooling2D(),

  layers.Flatten(),

  layers.Dense(64, activation='relu'),

  layers.Dense(32, activation='relu'),

  layers.Dense(1, activation='sigmoid')

])

Code snippet 4, model definition

Code snippet 4 demonstrates how the model was defined, first a normalisation layer this converts each pixel form a value ranging between 0 and 255 to between 0 and 1 and helps the model converge faster. Next is a convolution layer, earlier in the project a brief definition of a convolutional layer was given. To elaborate each filer consists of a kerel of weights. For the above layer the kernel is essentially a 3 by 3 matrix of with each index set to an arbitrary weight.

This convolution layer contains 32 filers, a kernel size of 3 by 3, same padding and using ReLU as its activation function. Each filter is moved over each pixel of the input which as the is the first convolution layer is simple a normalise fabric tile, the dot product is then computed where the filter and input overlap (Wu, 2017). Same padding specifies that the output of the layer should be the same size as the input adding padding if needed, this helps to preserve features making sure they can be processed by subsequent layers. This is then passed to a max pooling layer that reduces the size of the output while keeping the most important features, this process is repeated twice more using 64 filters.

After the third max pooling layer the output is passed to a flattering layer that convers the data from many dimensions to 1. A series of fully connected layers these reduce the output until only a single score between 0 and 1. As the project will classify images in a binary fashion, either defective or normal, the sigmoid activation function will likely be best suited for the final fully connected layer. The score represents the probability that the given tile is non defective. A score close to 0 mean the tile image is most likely contains a defect, a score close to 1 mean the image likely does not contain a defect.

Table - Dataset Breakdown

|  |  |  |
| --- | --- | --- |
| Set | Non-Defective Images | Defective Image |
| Training | 3719 | 673 |
| Validation | 816 | 151 |
| Test | 476 | 88 |

The above table details the size of the data sets the image was trained on, all the defective tiles were used however in an effort to stop bias and overfitting only 5000 of the 113,307 non-defective images were used. The models was then trained over 30 epochs during which the weights inside the filters of the convolution layers were adjusted, each epoch was evaluated on the validation set.

In an effort to produce a second more general model with possibly increased accuracy due to a larger training set data augmentation was used. Keras allows this done through a number of methods, this was implemented through the addition of two layers. A random flip layer and a random rotation layer as the names suggest a random flip layer randomly flips some images horizontally and the random rotation layer randomly rotates some images.

The model can then be used to predict the class an image by calling ‘model.predict()’ on either a single or an array of images. The confidence of each prediction was found by subtracting the absolute difference between the prediction and the closest class (either 0 or 1) from 1 then multiplying by 100.

## Sprint 4: Inspection Application and Human Testing Application

### Goals and Design Decisions

The goals of this sprint were developing a prototype inspection application and application to test the accuracy of human inspection. The inspection application will use the morphology inspection technique and the convolutional neural network. It must allow the user too:

* Import a set of images to be inspected.
* Choose which inspection technique is used.
* If the neural network inspection is chosen, the user can choose which model to use.
* Control the parameters of the chosen inspection technique.
* Graphical user interface, application

  Description automatically generatedView the defects found.

Figure - Inspection Application Wireframe

I chose to import images rather than connect to a live camera feed as it enables the user to quickly inspect a variety of fabric without having to reset a machine. While this would not be ideal in a production environment it is optimal for testing.

Graphical user interface

Description automatically generated with medium confidenceThe application to test human inspection should be simple, it should display several images in a random order some with defects and some without. For each image the user should select whether they believe the image to include a defect or not. The application should display how the user performed so it can be recorded. This application should be as minimal as possible as to not take up development time that could be used form more important tasks.

Figure - Human Testing Application Wireframe

I used PyQt to develop both as the use of the designer tool allows for rapid development.

### Implementation

#### Inspection Application

Graphical user interface

Description automatically generatedQT designer was used to create a basic layout for the application, consisting of a number of Qt widgets: labels (used to display both images and text), check boxes, spin boxes (allow the users to input numerical data) and button. Once converted into a python file these buttons, check boxes and spin boxes could be connected to functions.

Figure - Inspection Application User Interface

The image data is loaded after the user specifies the folder they are stored , no background removal is incorporated into this prototype so any images must have been pre-processed beforehand. The images are moved into main memory by listing all the file names in the specified folder and calling the OpenCv “imread()” function. This loads all the image at once enabling faster accesses when inspecting at the cost hardware utilisation.

The model used for the neural network inspection technique loaded at the applications startup. Two models are loaded both trained during the third sprint, one is trained on only a set of tiles and the other trained using the same set of tiles with data augmentation applied.

Inspection begins once the start button is pressed, an image is tiled and each tile run through the selected inspection techniques, an array of the defective tiles found is then returned and displayed to the user. Whenever the “next” button is pressed the next defect found is displayed to the user until all the defects in the list have been displayed. “Start” can then be repeatedly pressed to inspect images in turn each time displaying the defective tiles found.

#### Human Testing Application

This application was developed very similarly to the last. The filenames from two predetermined folders are stored in a list, they contain names of 8 defective images and 8 normal images. The user is then presented with a simple screen only contain a start button. Once pressed the application uses the time library of python to obtain the current time.

The start button is then hidden, the first image to be inspected by the user is displayed and the application wait for the user to press either the “defect” or “normal” button. When pressed the application checks whether the file name of the image being displayed belongs to the folder of defective or normal images and increments the appropriate variable out of “normalCorrect”, “normalIncorrect”, “defectCorrect”, “defectIncorrect”. Once all 16 images have been inspected these variables are displayed to the user along with the accuracy they achived

### Sprint Review

# Chapter 3: Results

The previous chapter focused on the implementation, but little thought was given to how these implementations could be analysed. This chapter will explain what methods were used to evaluate the performance of the various defect inspection developed. All testing was conducted using functions available from Matplotlib and Sklearn.

## Key Inspection Metrics

When analysing fabric inspection methods there exists three key metrics, general accuracy, catch rate and misidentification rate. A general accuracy when inspection from images can be calculated by the number of images containing defects correctly identified plus the number of images not containing defects correctly identified all over the total number of images. Catch rate can be described the number of defects caught dived by the total number of defects. Similarly, misidentification rate is the fraction of non-defective images that are identified by the inspection technique as defective. False positive rate and true positive rate will be discussed throughout the

section in terms of this project the false is equivalent to misidentification rate and true positive rate equivalent to catch rate.

While general accuracy can be informative when directly comparing inspection techniques it can also be misleading. Two techniques with the same accuracy may offer vastly different value to a fabric producer. A high catch rate is usually desired to ensure few defects make it through production and are sold to an end user however if this is achieved by allowing a high false identification rate then production could be slowed by unscary stoppages as defects will need to be recorded or removed.

## Human Inspection

To evaluate the effectiveness of the inspection methods developed and weather they would be advantageous to a fabric producer to implement, the project needed a baseline accuracy of current human inspection. The previous chapter explains how a human testing application was developed and how the testers used the application. After 8 testers analyse all 16 images (APENDIX\*\*\*) of defective and non-defective images the results are as follows. All tester names were kept anonymous, and all were shown the same 5 defective and 5 non-defective images before the test, giving them a baseline understanding. All testers were also supplied with consent forms (APENDIX\*\*\*) a copy of the project information form (APENDIX\*\*\*).

Table - Human Testing Results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Tester: | Accuracy (%): | Defects Correctly Identified: | Images Misidentified Defects: | Non-Defects Correctly Identified: | Images Misidentified Non-Defects: | Time Taken (secs) |
| 1 | 62.5 | 6 | 4 | 4 | 2 | 158 |
| 2 | 62.5 | 5 | 3 | 5 | 3 | 95 |
| 3 | 75.0 | 7 | 3 | 5 | 1 | 147 |
| 4 | 87.5 | 6 | 0 | 8 | 2 | 126 |
| 5 | 62.5 | 6 | 4 | 4 | 2 | 119 |
| 6 | 68.75 | 5 | 2 | 6 | 3 | 112 |
| 7 | 62.5 | 7 | 5 | 3 | 1 | 58 |
| Average | 68.75 | 6 | 3 | 5 | 2 | 116.4 |

The average accuracy obtained from the testers was 68.75% with a catch rate of 75% and a misidentification rate of 37.5%.

## Statistical Analysis

### Histogram Inspection

A picture containing text, screenshot, plot, colorfulness

Description automatically generatedThe histogram generation method presented in sprint two was used on two defective tiles to decide if it warranted further investigation.

Figure - Histograms of Defective Tiles

Figure 9 displays the two defective tiles (a) crease and (b) knot and the histograms generated.

When compared to the histogram generated in figure 8 many of the bins in the defect histograms have a higher number of occurrences. This seems reasonable as defects usually present as a large mass of similarly coloured pixels. These results proved the concept of a statistical analysis based approach.

### Statistical Analysis using Standard Deviation and Range

When applying statistical analysis using the standard deviation and rage of the pixel values in greyscale segments/tiles. The following tables by applying this method two defective and non-defective tiles.

Table - Ranges and Standard Deviations of Example Non-Defective Tiles

|  |  |  |
| --- | --- | --- |
| Normal Tile Number | Standard Deviation | Range |
| 1 | 16.448 | 81 |
| 2 | 16.736 | 85 |
| 3 | 11.917 | 70 |
| 4 | 18.832 | 94 |
| 5 | 27.395 | 128 |
| Average: | 18.266 | 91.6 |

Table - Ranges and Standard Deviations of Example Defective Tiles

|  |  |  |
| --- | --- | --- |
| Defective Tile Number | Standard Deviation | Range |
| 1 | 16.289 | 114 |
| 2 | 16.839 | 107 |
| 3 | 17.569 | 107 |
| 4 | 17.099 | 113 |
| 5 | 14.642 | 99 |
| Average: | 16.488 | 108 |

These results will be discussed further in discussion section, however this inspection technique proved to not offer a reasonable level of accuracy as so no further testing was deemed necessary.

### Statistical Analysis using Reduced Colour Space

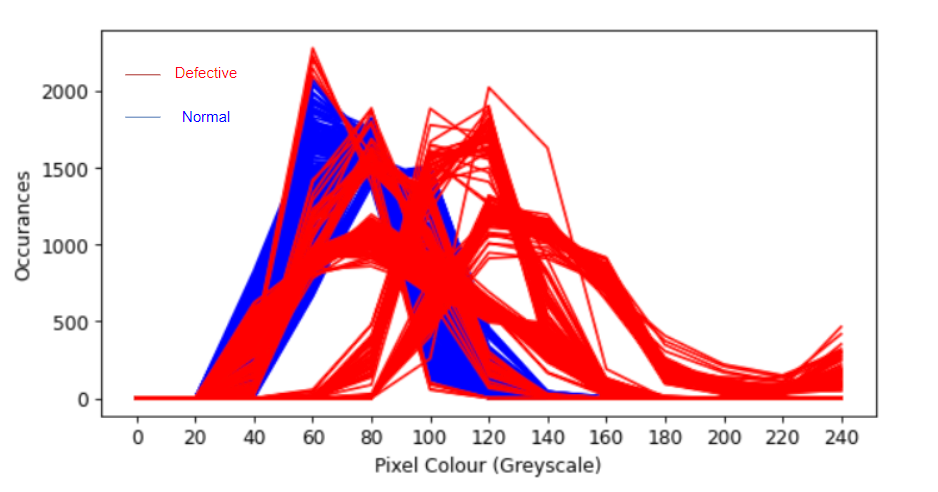
As described in the implementation chapter an attempt was made to detect defect in a tile based on the number of pixels with a certain value, once the colour space of the tile was reduced.

Figure - Reduced Colour Space Image Plot

A picture containing text, screenshot, diagram, colorfulness

Description automatically generatedFigure 16 depicts a plot of 500 random tiles split between normal and defective tiles, it plots then number of occurrences of pixels of specific values. The plot clearly shows that many defective tiles differ greatly at certain pixel values, some containing more at that specific value and some containing less. It was created by plotting the number of pixel occurrences against the list of reduced pixel values, these being [0, 20, 40, 60, 80, 100, 120, 140, 160, 180, 200, 220, 240] reducing the 255 colour space of the image to 14.

Figure - Reduced Colour Space Inspection Confusion Matrix

Figure 17 displays a confusion matrix formed by the statistical analysis detection method performed on 1000 known good tiles and all 909 defective tiles in the dataset. A confusion matrix is a particularly useful way of analysing the effectiveness of inspection methods, this is as all three of the key inspection metrics above can be ascertained from this single plot.

The data for this plot was generated by repeatedly running the “reduceInspect()” on two sets of tiles 1000 normal and 909 defect tiles. Two lists were created one consisting of targets and one of predictions. The targets represent the known state of images, that being either defective or non-defective/normal. For each image if it belongs to the set of normal images 1 is appended to the targets, 0 if it belongs to the set of defective images. If “reduceInspect()” function returns true for a specific image the image is predicted to be a defect and so a 0 is appended to the predictions list, a 1 is appended if the function returns false. Using the Sklearn “ConfusionMatrixDisplay.from\_predictions()” function a confusion matrix can be constructed from these targets and prediction. It achieved an accuracy of 49.475%, a catch rate of 94.49% and a miss misidentification rate of 91.6%.

The average execution time of the “reduceInspect()” function was 0.118 seconds, meaning that a master image containing on average 465 tiles would take 54.87 seconds to fully inspect. This average was found using the execution times from all 1909 tiles inspected to create the above confusion matrix.

## Morphology and Contour Finding Inspection

During the project 2 forms the morphology and contour finding inspection methods were produced, one using a the ‘findDefect()’ defect function and one using the ‘twoPassInspection()’ which as documented in the implementation applies the former function, inverts the image and applies the function again with the hope of finding defects missed in the first pass. This section will present the results for both implementations.

All results found used the same testing strategy as reduce colour space inspection. Each tile was tested individually with the chosen inspection technique and the targets and prediction lists were updated accordingly. Accuracy was also calculated in the same manner.

### Single Pass Inspection

Before parameter tuning single pass inspection the function used light blur kernel size of 5 by 5, a global threshold value of 110, an erosion kernel size of 5 by 5, a heavy blur kernel size of 15 by 15 and a minimum defect size of 100 pixels.

A picture containing text, screenshot, rectangle, colorfulness

Description automatically generatedUsing this set parameters, it achieved an accuracy of 75.327%, with each tile taking 0.000228 second to inspect meaning in the worst case an unsegmented image would take 0.106 seconds to fully inspect. Figure 18 displays the confusion matric obtained through this testing. With a catch rate of 72.06% and a misidentification rate of 21.7%.

Figure - Single Pass, No Tuning Confusion Matrix

While parameter tuning was done using the two-pass inspection method when applying the best parameters to single pass inspection the accuracy increased to 81.0896% and inspection time was unchanged the confusion matrix this created is presented in figure 19. Obtaining 78.77% catch rate and 16.6% misidentification rate.

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Figure - Single Pass, with Tuning Confusion Matrix

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Figure - Example Defects Not Caught by Single Pass

### Two Pass Inspection

Before parameter tuning using the same parameters as single pass inspection it achieved an accuracy of 76.637%, catch rate of 78.8%, misidentification rate of 27.1% and an execution time per tile of 0.000316 seconds. Meaning in the worst case an unsegmented image would take 0.147 seconds to fully inspect. As show by figure 21.

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Figure - Two Pass, No Tuning Confusion Matrix

After parameter tuning was complete the best parameters were found to be: a global threshold of 100, a light blur kernel size of 6 by 6, a heavy blur kernel size of 15 by 15, a erosion kernel size of 6 by 6 and a minimum defect size of 100 pixels. With these parameters this method achieved an 84.294%, catch rate of 89.99%, misidentification rate of 21.4%

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Figure - Two Pass, with Tuning Confusion Matrix

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Description automatically generated

Figure - Example Outputs Of Two Pass Inspection

However, these accuracies cannot be directly compared to those obtained through human inspection this is as humans inspect on complete images of fabric and not the individual tiles. To obtain accuracy that can be fairly compared to that of human testing the images used in human testing were tiled, each individual tile was the ran through the tuned ‘twoPassInspection()’ function and if even a single tile returned as defective the entire image was deemed defective. The same testing scheme was then applied using targets and predictions. On the same set of images human testers inspected this technique achieved an accuracy of 56.25%, catch rate of 87.5%, misidentification rate of 75% Figure 24. On the entire data set it achieved 49.19%, catch rate of 92.4%, misidentification rate of 83% Figure 25.

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Figure - Human Inspection Full Image Set Confusion Matrix

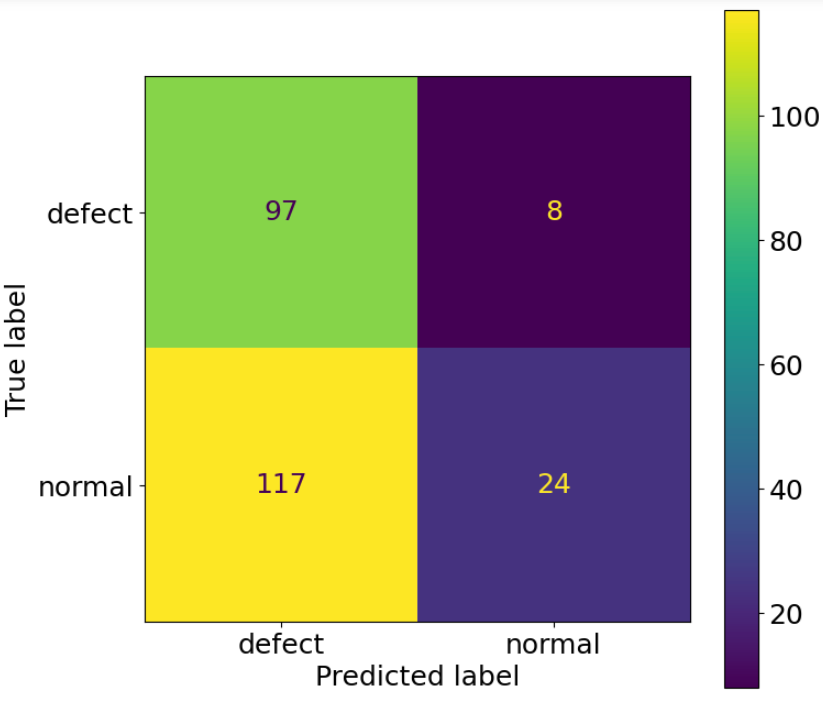


Figure - All Full Image Set Confusion Matrix

## Deep Learning Inspection

As discussed in the implementation the last form of defect inspection developed used a convolutional neural network trained to identify tiles containing defects. Two models were produced with using data augmentation and one without in this section I will discuss the effectiveness of both. During this section a number of other metrics were considered such as f1 scores, these can be used as a measure of accuracy and are less prone to bias than general accuracy.

### Convolutional Neural Network

The fist CNN produced used no data augmentation a after being trained on 3,719 non defective tiles and 673 defective tiles. Figure 26 displays the training and validation accuracy and loss throughout training.

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Figure - Training a Validation Accuracy

When prediction on the test data the confusion matrix in figure 26 was generated, producing an accuracy 98.76%, catch rate of 95.45% and a misidentification rate of 0.63%. Figure 27 displays the f1, precision and recall scores. With recall for the defect (0) class being equivalent to catch rate.

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A picture containing screenshot, text, rectangle, colorfulness

Description automatically generated

An ROC (receiver operating characteristic) curve can be used to find a classification threshold that minimises the rate of false positives while maximising true positive rate. Figure \*\* presents this curve.

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Description automatically generated

This curve was created using sklearn ‘metrics.roc\_curve()’, the metrics returned by this function pointed to an optimum threshold of 0.96. When using this value to determine classification accuracy reduced to 98.0%, catch rate 96.6% and a misidentification rate 1.68%. The model was further tested with a threshold value of 0.15 designed to minimize misidentification rate, lowering it too 0.42% and increasing accuracy to 98.76% but in turn decreasing catch rate to 94.4%.

However as mentioned before these measures are calculated when classifying individual tiles, when applied to full images using the rule that a single defective deems the entire image as defective. The highest accuracy obtained when inspecting the same image set as the testers was 62.5% and was obtained when using the threshold of 0.15. It achieved a catch rate of 75% and a misidentification rate of 50%.

When applied to all images the best accuracy was gained using the threshold 0.15 at 71%.

### Convolutional Neural Network Using Data Augmentation

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Figure \*\* shows the training and validation accuracy and losses over 30 epochs of training with data augmentation applied on the same dataset producing an accuracy of 98.23%, catch rate of 89.8% and a misidentification rate of 0.21%.

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A picture containing text, screenshot, line, plot

Description automatically generated

The optimum threshold produced by the roc curve was 0.928 when applied accuracy was unchanged and misidentification rate rose to 1.68%, however catch rate increased to 98%. Lowering the threshold to 0.15 produced worse results in all categories that the standard threshold of 0.5 used after training. When testing using the same full images as the testers the best result of accuracy 56%, catch rate of 38% and misidentification rate of 25% was produced with a threshold of 0.15. Straggly using the optimum threshold of found produced a 100% misidentification rate and catch rate was observer on both the set of images shown to tester and all the images in the dataset. When using a more accurate 0.15 threshold on all image’s accuracy increased to 66%.

A picture containing pattern, screenshot, text, rectangle

Description automatically generated

Each full image took an average of 3.7 seconds to inspect meaning all 16 tester images would have taken 59.2 seconds to inspect.

## Prototype Inspection Application

As this application was developed in only a single sprint it was not tested extensively as was used to instead offer a proof of concept of what an inspection application may look like. However, the application was shown, and a demonstration was given to all 7 individuals that took part in the human inspection test. Five agreed that the operating the application was intuitive and that it presented the feedback they would expect, this being the defects found. Two questioned why the application inspected a single image at a time pointing out that it would be tedious to use for any extended amount of time, this was done to allow for debugging but would not be optimal in a production environment.

# Chapter 4: Discussion

This chapter will discuss and evaluate the results found in the previous chapter. Here the methods will be compared both too each other and the value they could deliver if implemented in a commercial sense.

## Evaluation

### Human Inspection

The application created to gather the results of human inspection wasn’t optimal in realty human inspection would not be completely visual and larger regions could inspect at a single time. Despite the accuracy found almost completely mimicked figure taken from the industry varying from 60%-70%. While some individuals achieved higher accuracy in my application, they were only tested on 16 images if this expanded upon the tedious nature of jobs would have likely lowered their accuracy.

Statistical Analysis Based Inspection

At first statistical analysis seemed promising, when comparing the histograms in figure 9 to the histogram in figure 8 many of the bins in the defect histograms have a higher number of occurrences. This seems reasonable as defects usually present as a large mass of similarly coloured pixels, for these reasons it was developed further. This was further reinforced by table 3 and 4 which showed a clear pattern that the standard deviation of a tile was lower if the tile included a defect however these defective tiles also had a higher range, these measures seem to contradict themselves. There also existed outliers that broke both conventions in either table hence a detection method was not produced using only these metrics. It is likely that both the histograms and tables are misleading due to there small sample size and the project should not have treated them as representative of the larger dataset. Figure 16 clearly indicates that when colour space is reduced many defective tiles differ greatly at certain pixel values. For example, many defective tiles contained over 1500 pixels with value 140 whereas no non-defective tile had over 100 pixels at the same value.

However, despite the seemingly clear distinction between defective tiles and non-defective tiles a low accuracy was produced by the reduced colour space inspection technique. A 49.4% accuracy is what would be expected from an algorithm that randomly decided a class, the key problem was the extremely high catch and rate misidentification rate. This indicates that rules that decided defect classification were incorrectly chosen, classifying almost every image as defective. The nature of the fabric chosen for the project may have also played a part in reducing the accuracy of this method as shadows and highlights distort monotone image far more than colour images, a similar method used successfully on colour fabric as the red, green, and blue channels can be inspected separately (Rasheed, 2020).

Overall, this technique produced results that were worse than human inspection with the time to inspect each full image of 54.87 seconds due to the sequential implementation when reducing the image’s colour space, it would be a slower than human inspection by a factor of 7.5.

### Morphology and Contour Finding Inspection

This inspection method proved to be far more effective than a statistical approach with both single and two pass inspection obtaining a higher accuracy. (Figure 18) demonstrates the largest improvement being the misidentification rate dropping to 21.7% while keeping a relatively high catch rate even before the parameters were tuned. Figure 20 displays the problem described in earlier sections where single pass inspection ignores lighter defects, while two pass inspection eradicates this issue but does not necessarily mean it is superior in a commercial environment. If the specific fabric to be inspected is prone neps, fuzzy balls and knots and lighter defects such as broken yarns are rare then the faster speed of single pass inspection may be desirable. The times to inspect full images are very similar so in most cases the higher catch rate of two pass inspection will be optimal.

Unfortunately, even with parameters tuned to the misidentification rate on full images is unacceptable high leading to lower accuracy then human inspection. This is as due a single tile misidentification rate of 21.4% meaning that out of an average of 465 tiles in a single image approximately 100 tiles will be miss identified as defective. Testing further show that the method struggles with defects a similar colour Hence this current implementation could not be used for fully autonomous inspection. A key advantage this form of inspection offers over both a statistical and deep learning approach is shown by its output (fig \*\*) as returns the contour surrounding defect this can be used a visual aid to assist a human inspector or used to classify the defects.

### Convolutional Neural Network Inspection

A convolutional neural network inspection approach performed far better than either of the two previous methods however it was by no mean perfect. As seen by the training by the high training accuracies and slightly lower validation accuracies the first models were slightly overfit, however the almost identical validation and training accuracies and losses produced by the second model showed that the data augmentation worked as intended eradicating this overfitting and creating a more general inspection technique. Despite this on the test set both achieved a very similar accuracy with the catch rate of the second model being over 5% lower. It is likely that this second model is underfit due to the random rotation layer included, all images of fabric must have the weave run perfectly vertically any rotation in this would be classed as a defect. By including this rotation, we are confusing by telling to ignore a rotation in the weave in turn lowering catch rate.

Unfortunately, this high individual tile accuracy is carried into full image inspection. Here it performed as well as most human tester, it did produce slightly higher catch rate than humans but also high misidentification rates. This likely due to bias in the training data, cotton incorporated splits defects into a number of classes three of which are line, pattern and isolated. As line and pattern defects are large when the full images were segmented into tiles a single defect would result in a number if tiles unfortunately the same could not be said for small, isolated defects such as knots. We can see in fig \*\* that this bias negatively affected the ability of the model to recognise these isolated defects reducing catch rate. Another reason for lower accuracies on full images is that even with sub 1% misidentification out of a possible 465 tiles per image it is likely at least one tile will be miss identified as defective tainting the entire image.

With an average full image inspection time of 3.7 seconds and an accuracy of 71% the solution performs almost identically to human inspectors and so this inspection technique could be a candidate for use as a fully automated system. It is worth considering that this testing was done on a system without a GPU and with the highly parallel nature of a CNN, inspection times could be reduced by up to a factor of 100 (Chaubal, 2022) this would make it more effective then human inspection.

### Conclusion

In conclusion all the project’s aims were achieved, three inspection techniques were produced as well as prototype application to enable users to apply two of these methods. All were compared not only each other but the current human inspection solution and each was found to have value in commercial use. Statistical analysis if used with a different dataset of coloured images could be used to autonomously inspect, morphological inspection while currently not achieving the accuracy needed to autonomously inspect its speed means could be a useful tool to aid human inspectors increasing their accuracy. Finally, CNN inspection showed promise in its ability to outperform all other explored forms of inspection, with little further development needed to reach this. All testers saw the value in the final application produced and understood how it may be used and pointed that that inspecting multiple images at once would increase its value.

## Future Directions

If the project were to be continued most effort should be placed into further increasing accuracy and refining the inspection application. There a many ways accuracy could be increased, through a statistical approach plotting average pixels values along the x and y axis looking for peaks and troughs would likely be more effective than the methods produced during the project, it would also allow the location of defects to be found. Morphology inspection could also be improved as size of the kernels used for opening and closing were static and not tuned this could added and would hopefully improve accuracy. In both CNN and morphology inspection if even a single tile was seen as defective the entire image was treated as such, a condition could be placed on this needed a certain number of tiles to be defective possibly reducing misidentification rate.

Several small tweaks like ones above could be implemented but the greatest improvement to accuracy would be made by increase size and variety of the dataset. With hundreds or even thousands more labelled images the first two inspection techniques could be tuned and optimised more effectively. This have the largest impact when training new models, a respectable accuracy was achieved with a small data set so is unreasonable to a expect and excellent accuracy with a much larger data set with less bias. The images used in CNN could be reduced in size for 64 by 64 to 16 by 16 as long this does not remove defects it could lead to similar accuracy with vastly reduced inspection times. If all these changes worked well then, a combined approach could be explored, using image morphology tuned for high catch rate as an initial screening step thanks to its high speed, a CNN model could then inspect only tiles it flags as suspicious lowering the overall time to inspect.

In the long term the prototype inspection application should be moved from a system where a batch of images loaded in then inspected to one connected to a live camera. This would enable it to inspect images in real time and would be the final step needed to create a full autonomous inspection system.

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# Appendix A Self-appraisal

## Critical self-evaluation

Overall, I am stratified with how the project went as it achieved its aims. Unfortunately, accuracies were lower than anticipated, I attribute this to spreading myself too thin. Perhaps spending my focused one inspection technique would have afforded me enough time to develop a more comprehensive final inspect application. This would have limited my ability to compare different and may have led me down a dead end, so I do believe my approach to the project was correct but lacked effective time management.

While I have a had experience with coding projects a report of this scale was complexly new and posed challenges I wasn’t fully prepared for. From the start of the project, I had clear vision the steps involved and exactly what I wanted to achieve. The background reached conducted reassured me that most these goals were achievable, however when finding a dataset to use there were few options with the AITEX dataset being the most promising but still small.

After initial prototyping and the completion of deep learning tutorial I realised that my ideas to not only identify defects but then classify them unachievable win time span and with the data available. In the end I am glad I limited myself to defect identification it allowed me to explore the subject in more detail and produce an effective final solution. The initial sprints when well and development was fast, this ended when testing began in April which took far longer than anticipated and place be behind when starting the report, in hind sigh the report should have been written in tandem development.

I am happy with code produced and the results gather, I believe the code was written to a high standard, all inspection methods function as expected and the final application was intuitive to use. I would have liked enough time to perform more tuning on the inspection methods, this being said I not unsatisfied with any of the results as the projected focused was to compare the methods not achieve the highest accuracy possible.

### Lesson Learnt

I believe this project has allowed grown as a computer scientist, it has developed my ability to critically evaluate the academic work of others to help build my own ideas and avoid pitfalls. It allowed to become comfortable with a number of industry standard computer vision a deep learning tools and libraries. Cementing my interest in these areas and building a skill set I can take into employment after graduation. In particular it has taught me how to properly assess deep learning techniques, allowing me to identify overfitting and bias and to critically think about role of data augmentation, both its benefits and disadvantages.

Since the start of university, I have been confident in my ability to write essays and reports quickly. This projected has questioned whether I was overconfident in this regard and has given a new respect for those who have masted time management and can minimise procrastination, areas of myself I have now identified need work. I now understand that the importance of documenting software development, it allows you to analyses the decisions made during implementation and whether different more effective methods exist.

## Legal, social, ethical and professional issues

### Legal issues

The project extensively uses a number of libraries including matplotlib, tensorflow, OpenCV and sklearn all of which are free to use in any personal and commercial sense without limitation and so covers all content within the project.

All training, testing and general development was done using the AITEX public defect database which is free to use for research purposes. It was created by Javier Silvestre-Blanes, Teresa Albero-Albero, Ignacio Miralles, Rubén Pérez-Llorens and Jorge Moreno.

Dataset:

<https://www.aitex.es/afid/>

Paper:

[https://www.autexrj.com/cms/zalaczone\_pliki/[23000929\_-\_Autex\_Research\_Journal]\_A\_Public\_Fabric\_Database\_for\_Defect\_Detection\_Methods\_and\_Results.pdf](https://www.autexrj.com/cms/zalaczone_pliki/%5b23000929_-_Autex_Research_Journal%5d_A_Public_Fabric_Database_for_Defect_Detection_Methods_and_Results.pdf)

If this project was further developed for commercial use the consent would need to be gained from the creators of the dataset or a new model would need to be trained from a new set of images.

### Social Issues

As the current project is purely research focused it poses no social issues. However, if it was taken forward and used commercially it could have large social ramification. As with any form of automation there is the possibility for machines to replace human workers and increase economic inequality.

A commercial application could increase defect catch rate over current solutions increasing the amount of waste generated.

### Ethical Issues

A number of testers were used to gain an insight into the accuracy of current solution. To ensure the projected remained ethical all testers were given a project information sheet (appendix E) and signed a consent forms (appendix D). They were shown an ample number of example defective and non-defective images, allowing them to make comfortable and informed decisions when being evaluated.

Testers could withdraw any time and the results gather form them were anonymised to protect their privacy.

### professional issues

The projected was developed with goof professional practices in mind, git lab version control was used through, and most coding was done through jupyter notebook allowing it to be documented and separated under headings. All external material has been correctly credited.

# Appendix B External Materials

# Appendix D User Testing Consent Form

# Appendix E Project Information Sheet

# Appendix F User Manual