

**FABRIC DEFECT DETECTION USING ONE-CLASS  
CLASSIFIER**

V.K.N.Madhusanka

199476R

Degree of Master of Science in Artificial Intelligence

Department of Computational Mathematics,  
Faculty of Information Technology

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## **DECLARATION**

I declare that this dissertation doesn't include, without acknowledgment, any content submitted for a Diploma or a Degree at any institute, and that it does not contain, to the best of knowledge and believing, any material previously released or written by another person or myself, except where suitable citations are made in the text.

I also offer my consent for my dissertation to be photocopied and interlibrary loaned if it is accepted, and for the title and description to be made available to outside organizations.

Name of the student

V. K. N. Madhusanka

Signature of Student

Date:

Supervised by

Dr. Subha Fernando

Signature of the supervisor

Date:

## **Abstract**

Textile is wide, very important in critical industry, because it provide lot prodcut to the human day to day life. As example cloths, wipes, transportation materials, wipes, hosuning materials etc. Then quality of the products are very important for their demand. Therefore defect identification during the production is very importat and then they can maintain better price for their production. Therefore fabric defect detection and identification is a very impotant part of the textile industry's quality control process. Currently, there are many manualinspection method to identify defects and, to enhance the efficiency, it is needed to repace manual inspectionmethod bby a automatic inspection method.

Machine vision is diversifying and expanding in defect detection using deep learning. Traditional systems like detecting and classifying defects using image segmentation, defect detection and image classification have some limitations like requiring a lot of defective data to the training process and needing pre-identification of defects in the datasets. However, it is very difficult to get a large amount of actual data with defects and real-time processes.

The one-class classifier is a classical machine learning problem that has received considerable attention recently for fabric defect detection. Tin this scenario, only non-defective class data are available in the training process and avoid the requirement of defective to train process. However, State of art models in deep neural networks with one-class classifiers is still unable to record higher accuracy.

This research proposes our approach, for identifying defective fabric using features of the non-defective fabric with higher accuracy. The implications of this research can be an initiative to such applications. That approach consists of a VGG-16 pre-trained framework and trainable network with a new Loss function for increase accuracy of defect detection.

## **DEDICATION**

To my parents for their dedicated partnership in the success of my life

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## Abbreviations

ANN	Artificial neural network
CNN	Convolutional neural network
SVM	Support Vector Machine
OCSVM	One-class Support Vector Machine
VGG	Visual Geometry Group
DCNN	Deep Convolutional neural network
GPU	Graphics Processing Unit
VGGNet	Visual Geometry Group network
PB-OCSVM	Pinball - One-class Support Vector Machine
RLOCSVM	Ramp Loss One-class Support Vector Machine
ROCSVM-RHHQ	Robust One-class Support Vector Machine based on rescaled hinge loss function
CCP	concave -Convex Procedure
SVDD	Support Vector Data Description
SAD	semi-supervised anomaly detection
UCL	Upper control limit
LCL	Lower control limit
AUC	Area Under the Curve
OCSTM	One-class Support Tensor Machine