Gripper-Enhanced Fabric Cut Piece Sorting System based on Defects

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Abstract**—** *Sri Lanka's garment industry is crucial, contributing significantly to the country's export market. However, current fabric handling methods in Sri Lankan companies are primarily reliant on manual labor, creating a compelling potential for research and development in the field of automated fabric handling. Fabrics present distinct challenges due to their dynamic and static character, needing novel solutions to overcome these limitations. Furthermore, human fabric problem detection achieves just 60% accuracy, emphasizing the importance of automation in this vital sector. Significant benefits can be obtained by automating these processes in textile manufacturers.The fundamental goal of this project is to design and build an innovative system capable of automatically separating and classifying cloth cut pieces based on the presence of defects. Our suggested device includes a cylindrical manipulator outfitted with cutting-edge pinch-like grippers designed exclusively for effective ply separation. To improve defect detection accuracy, we use a custom-trained convolutional neural network (CNN) with a validation accuracy of 80%. We have also created a simple platform for remote control and real-time monitoring of the entire system by using IoT technology.This complete project not only meets the critical demand for fabric handling automation, but it also has the potential to change the garment manufacturing process in Sri Lanka.*

Keywords**— Automated fabric handling, fabric defect detection, convolutional neural network, pinch gripper**

I. INTRODUCTION

A. Background

The apparel industry is Sri Lanka's largest industrial export and earned $5.95 billion in 2022, accounting for more than 52% of the country's total export earnings (Reuters, 2023). The industry is also the country's largest net foreign exchange earner since 1992 (Statista, 2023). While various parts of garment manufacturing plants have adopted automation to improve the efficiency of their operations, one noteworthy area that is yet to witness automation involves handling of fabrics at various stages.

In a garment factory, approximately 20-30% of the total labor cost is accounted for by material handling, and in a sewing room, approximately 80% of the time is spent on material handling (Sarkar, 2016). One of the main research in the apparel sector relates to the automation of fabric processing. The main component of clothing is fabric, which needs to be transferred from one process to another in many processes. In order to move the fabrics, they need to be fixed by suitable devices and transferred to movable components and then replaced for another operation. Achieving automation in clothing manufacturing involves addressing critical challenges:

i. Versatility in Fabric Handling: The automation system must possess adaptability, enabling it to effectively work with a wide range of fabric types, accommodating variations in composition, thickness, and texture.

ii. Gentle Fabric Treatment: Ensuring that the automation process handles fabrics delicately, without causing any harm or deformation, is imperative. Preserving the structural integrity and appearance of textile materials is a top priority.

iii. Precision in Fabric Manipulation: Maintaining a high level of precision is essential. The automation system must exhibit the capacity to accurately control fabric movement, alignment, and positioning, meeting the stringent requirements of clothing production.

Due to these reasons, there has been little progress in material handling in apparel industry.

Defect identification is another critical operation in garment factories, as 85% of product rejections can be traced to fabric-related issues, resulting in significant reductions in sales prices (Arıkan, 2019). Existing manual fabric defect detection methods involve moving a piece of fabric on a drum against a backlit background, with an inspector carefully examining the material as the drum rotates. This process runs at approximately 8-20 meters per second, and disappointingly, only 60% of defects are successfully identified (Arıkan, 2019). Therefore, manual inspection methods are widely considered to be time-consuming and lack precision (Habib et al., 2014).

The primary aim of this research project encompasses several key objectives. Firstly, it seeks to develop an efficient gripping method tailored for the handling of individual fabric plies. In addition, the project aims to design a specialized manipulator capable of accurately picking and placing fabric pieces. Furthermore, a critical aspect of this research is the creation of a system equipped with the ability to detect selected defective cut fabric pieces. Finally, the project endeavors to establish a mechanism for discarding any cut fabric pieces identified as defective. These objectives collectively contribute to the overarching goal of improving the precision and quality of fabric handling and processing.

II. METHODOLOGY

The current processes of fabric manipulation and defect detection was observed in several Sri Lankan garment factories. In Sri Lankan factories, fabric ply separation is done manually. After the fabric pieces are cut, the stacks are placed on shelves and manually transported to the sewing tables in stacks. It was also observed that storing fabrics in piles for extended periods has caused the edges to curl up and wrinkle.

The fabric defect detection in garment industries is done before the fabric cutting process (Li et al., 2021). Fabric bulk sheets are sent through manual fabric inspection machines, where an operator is constantly inspecting for defects. This method as reviewed through literature as well is found to be only 65% accurate, and is also a time consuming and monotonous task. It was noted that no fabric inspection was done after the cutting process which has the possibility of creating defects in fabrics such as holes, tears and oil stains.

The methodology employed for the decision-making process involved a comprehensive literature review, and a morphological analysis with a primary focus on two critical aspects: the system's ability to accurately separate fabric plies and its proficiency in defect detection, including the identification of defect types. We carefully considered these vital factors for identifying the most suitable combination of gripping mechanism, motion control, defect detection method, and sorting approach. To further refine the decision-making process, numerical values were assigned to ten key design factors, each rated on a scale of 1 to 10, representing its importance in the evaluation process. These factors include Accuracy, Cost, Maintainability, Speed, Safety, Space, Durability, Flexibility, Computational Power, and Power Consumption. The Pugh Matrix was employed to objectively compare these combinations based on these factors, which allowed to make a well-informed and systematic choice that balances the diverse requirements and priorities of the project. The combination that scored the highest in the Pugh Matrix was selected as the most suitable design option, aligning with the project's objectives and constraints.

In addition to the literature survey done on the fabric gripping techniques, a few experiments were also done to test the functionality of a few methods such as pneumatic(vacuum), pinching and electrostatic.

Pinch grippers proved to be the best option for guaranteeing secure and precise fabric piece grabbing (Koustoumpardis et al, 2004), while the use of a cylindrical manipulator offered the essential motion control for seamless material handling (Universal Robots, 2023). A Convolutional Neural Network (CNN) was used to tackle the critical task of defect identification, leveraging its exceptional capabilities to discover and categorize fabric defects with an acceptable precision. Finally, a rotatable platform was added to aid in the effective sorting of fabric pieces based on their fault status. These carefully selected concepts operate in tandem to change the fabric handling process, improving efficiency, quality control, and overall productivity in the garment business.The proposed process flow is as shown in Figure 1.

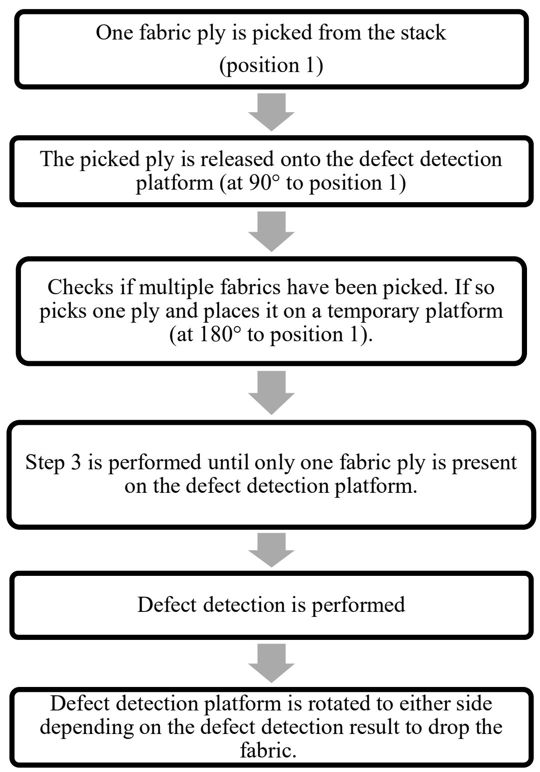
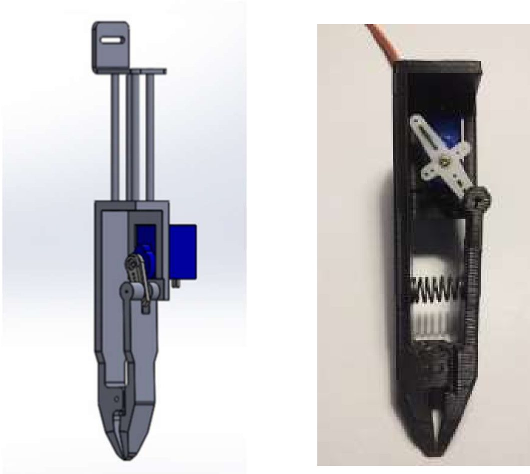


Figure 1- process flow of the designed system

A. Mechanical Design

1) Gripper: The pinch gripper was made to actuate using a servo motor and the gripper dimensions were scaled based on the size of the servo motor. Figure 2(a) shows the CAD (Computer-Aided Design) model of the gripper. The gripper was printed using Nylon which is less brittle and it was printed horizontally so that the force on the arm acts perpendicular to the layers and has no tendency of sliding over each other. Figure 2(b) shows the fabricated gripper.



(a) (b)

Figure 2 –(a) CAD model of gripper (b) fabricated gripper

2) Manipulator: A two D.O.F manipulator was designed with linear vertical movement achieved by a ball screw linear actuator and rotation by a stepper motor coupled with two timing wheels to increase the torque. The manipulator consists of a base plate, rotating shaft, rotating bed, vertical and horizontal Al profile bars, ball nut, screw shaft, sliding plate with wheels, gripper plate and gripper brackets. Figure 3 shows the CAD model of the manipulator.

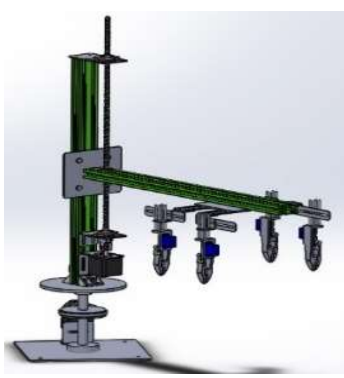


Figure 3 – CAD model of manipulator

The grippers were placed at four corners to pick and place the fabric piece wrinkle free. The gripper brackets were made so that the gripper positions are variable in both X and Y directions to adjust to different sizes and shapes of fabric pieces. Figure 4 shows the adjustable brackets.

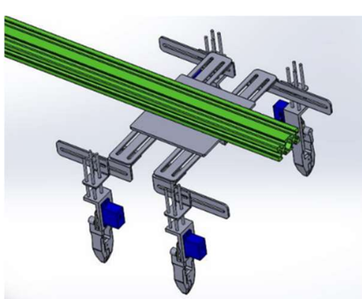
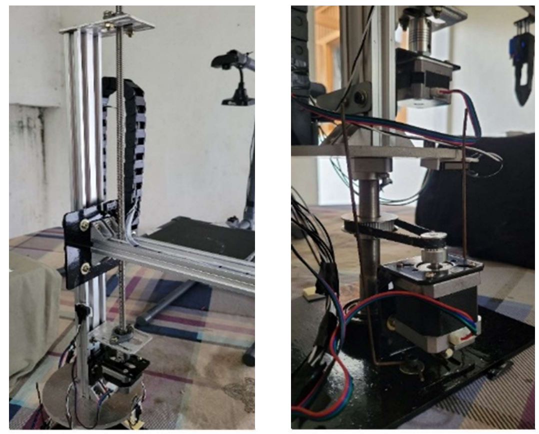


Figure 4 – adjustable gripper brackets.

To allow for free vertical movement, rather than the conventional linear guides and linear beraings, a plate with four wheels that are compatible with the grooves in the Al profiles were used in order to reduce both the weight and the cost. Figure 5(a) shows how linear vertical motion is achieved and Figure 5(b) shows how rotary motion is achieved in the manipulator.



(a) (b)

Figure 5: (a) – vertical motion, (b) – rotary motion.

B. Calculations

1) *Ball Screw Linear Actuator:* calculations of lead angle accuracy, screw shaft diameter and length, ball nut model and required motor torque were done in reference to the Ball screw THK general catalog.

2) *Balancing of manipulator:* the static and dynamic balancing of the manipulator were done as follows.

All the weights on the horizontal Aluminium profile arm are supported by the screw shaft, therefore when taking the moments about the central rotation axis all the weights not through the central axis acts through the stepper motor connected to the screw shaft. Hence, the distance of the load from the central axis is the distance of the stepper motor from the central axis (4.65 cm) as shown in Figure 6. Here, m is the total weight of the system (grippers + gripper plate + horizontal Al profile + screw shaft + motor + moving table).

$$m = 0.8 + 0.0749 + 0.4 + 0.188 + 0.23 + 0.3 = 2.0 \text{ kg} \quad (1)$$

Therefore, to balance the moments about the central axis another 2kg weight is attached to the opposite side of the axis at a distance of 4.65 cm. This balances the manipulator statically.

Since both sides of the axis rotate at the same speed(ω_1=ω_2), and after statically balancing it(m_1r_1=m_2r_2), the centrifugal force($m\omega^2r$) exerted on both sides will be equal. Therefore, the system is dynamically balanced as well.

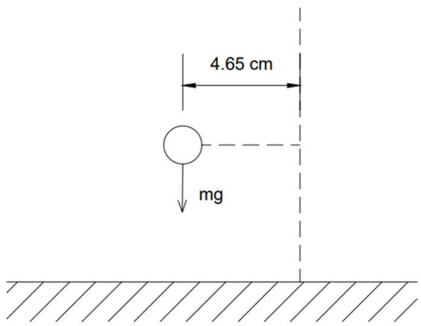


Figure 6 - Moment acting about central axis

3) *Motor torque for manipulator rotation:* First the moments of inertia of all components were found around their own axes (I). Then using parallel axis theorem, the moments of inertia of the components about the main rotational axis is found (I_a). General equations for Moment of inertia of cuboid and cylinder was used for calculations. Several assumptions were made. That is (1) All Al profile bars are considered as perfect solid cuboids and (2) Screw shafts are considered as perfect solid cylinders.

Considering a rotation of 90° in 0.5 s, the angular acceleration was calculated as π rads/s^{-2}. Then the torque (T) was obtained as 0.56Nm.

A. Defect Detection

1) Types of defects: For our project scope, we have considered two types of defects: holes and tears as these are commonly occurring defects and have a high tendency of occurring during the cutting process. Therefore, our system would classify the fabrics into three classes: Non defect, holes and tears.

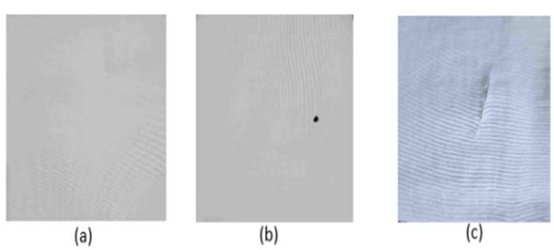


Figure 7 – Sample images from dataset (a): non-defect, (b): hole, (c): tear

2) Dataset: A dataset is required to train the Neural Network model and due to the unavailability of a suitable dataset online, a custom dataset was created by us. This was done by cutting the fabric into 15cm x 15cm pieces and making holes and tears on them. 60 pieces of each defect and another 60 for non-defect was made. To further increase the data, adjustments were done to the images such as orientation, contrast, and brightness changes to get approximately 200 images from one class to make a dataset of total 600 images.

3) Data preprocessing: before the dataset is used in training, the data was modified into a suitable format. The following preprocessing steps were done to achieve this: image resizing, color conversion, creating rrays and normalization.

4) CNN Architecture: the best combination of convolution layers, activation functions, pooling layers, dense layers and dropout layers were used with best number of layers, neurons and dropout perecentages used. The best combinations were achieved by using hyper parameter tuning from the keras tuner. Figure 8 shows the details of the final model.

5) Validation of the model: After considering the validation graphs of numerous models while optimizing them at each step, the best validation graphs obtained are shown in figure 9. Figure 9(a) shows the training accuracy and validation accuracy against the number of epochs. This model has obtained a validation accuracy of about 80%. Figure 9(b) shows the training loss and validation loss against the number of epochs. The validation loss has decreased gradually along with the training loss to a minimum of about 0.05. This can be considered good as it had an acceptable accuracy as well as a good generalization, and no overfitting or underfitting were observed. Therefore, this model was selected as the best and the weights of this model were used in prediction.

6) Taking predictions: to take predictions from the trained model, first the proper image has to be extracted since the raw image captured from the web camera also contains the background. The contours of the image captured from the web camera were marked and the largest contour (being the fabric piece) was selected. The outlines of the largest contour are then offset inwards from each side by 20 pixels to ensure no background is extracted. This is done because

Layer (type)	Output Shape	Param #
conv2d_17 (Conv2D)	(None, 222, 222, 256)	2560
activation_16 (Activation)	(None, 222, 222, 256)	0
max_pooling2d_16 (MaxPooling2D)	(None, 111, 111, 256)	0
conv2d_18 (Conv2D)	(None, 109, 109, 64)	147520
activation_17 (Activation)	(None, 109, 109, 64)	0
max_pooling2d_17 (MaxPooling2D)	(None, 54, 54, 64)	0
flatten_8 (Flatten)	(None, 186624)	0
dense_24 (Dense)	(None, 128)	23888000
dropout_16 (Dropout)	(None, 128)	0
dense_25 (Dense)	(None, 64)	8256
dropout_17 (Dropout)	(None, 64)	0
dense_26 (Dense)	(None, 3)	195

Total params: 24,046,531
Trainable params: 24,046,531
Non-trainable params: 0

Figure 8 – Model summary

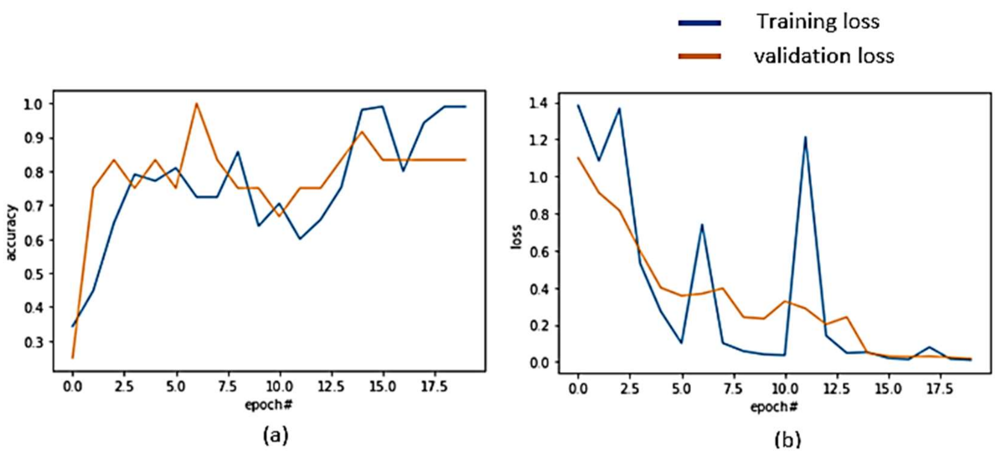


Figure 9: (a) Training accuracy and validation accuracy against the number of epochs (b) training loss and validation loss against the number of epochs

the fabric edges might not always be perfect straight lines which will cause the background to be included in the contour box. This ectracted image is then fed to the trained CNN model to get the prediction.

III. RESULTS

A. CNN Model

The CNN developed for defect detection was tested against 30 images. For these images, an overall accuracy of around 70% was obtained for the detection of whether it is a defect or not (binary classification). For the further classification according to the type of defect the accuracy obtained was around 65%. It was observed that the hole defects always were classified accurately as a defect while the smaller tear defects tended to be classified as non-defect, which is what accounts for the loss in the overall accuracy of the CNN model to 70%.

B. Gripper

During the testing of the gripper, it was observed that one of the major factors affecting the gripping of a single fabric ply is the horizontal alignment of the fabric stack. If the fabric stack is slanted, and hence making one side of the stack higher than the other, this will cause two grippers on the side of the higher stack to be pressed to the stack more than the two grippers on the other side. This will then result in the grippers on the higher side pinching into one fabric ply while the other side is not pressed enough to create the necessary friction to pinch one ply. Thus, a single fabric ply will be lifted but only from one side. Therefore, the platform on which the fabric stack is placed should be well levelled. Fifty test runs were conducted and overall, the grippers have an accuracy of around 80% in separating one fabric ply from the stack.

C. Manipulator

The major issue encountered during the testing of the manipulator is the jerking and significant vibration of the stepper motors. This occurs due to poor tuning of the stepper motor and can be resolved using a PID tuner.

IV.CONCLUSION

This project was to develop a prototype of an automated system to unstack a pile of fabric cut pieces and sort them based on presence of defects for the use in the garment industry. The two major challenges in this project were to develop grippers to grip a single fabric ply from the stack and to develop an algorithm to distinguish defective fabric pieces from non-defective ones.

In this system the gripping was achieved using pinch grippers and the method used for defect detection was convolutional neural networks. The system was designed and fabricated accordingly with a cartesian manipulator for the movement and then tested.

REFERENCES

Reuters. (2023, May 3). Sri Lanka apparel exports to drop by $1 billion in 2023, trade body says. *Reuters*. Retrieved from https://www.reuters.com/markets/asia/sri-lanka-apparel-exports-drop-by-1-bln-2023-trade-body-2023-05-03/

Statista. (2023, September 27). Apparel - Sri Lanka | Statista Market Forecast. *Statista.* Retrieved from https://www.statista.com/outlook/dmo/ecommerce/fashion/apparel/sri-lanka

Dheerasinghe, R. (2009) ‘Garment Industry in Sri Lanka Challenges, Prospects and Strategies’, *Staff Studies*, 33(1), p. 33. Available at: https://doi.org/10.4038/ss.v33i1.1246.

Sarkar, P., (2016), *Online Clothing Study*. Different Kind of Material Handling Systems Used in the Garment Industry. https://www.onlineclothingstudy.com/2016/06/different-kind-of-material-handling.html

Arıkan, C.O. (2019) 'Developing an intelligent automation and reporting system for fabric inspection machines', *Tekstil ve Konfeksiyon*, 29(4), pp. 86–93. Available at: https://doi.org/10.32710/tekstilvekonfeksiyon.491362.

Habib, M.T., Faisal, R.H., Rokonuzzaman, M. and Ahmed, F., (2014). Automated fabric defect inspection: a survey of classifiers. *arXiv preprint* arXiv:1405.6177.

Li, C., Li, J., Li, Y., He, L., Fu, X. and Chen, J., (2021). Fabric defect detection in textile manufacturing: a survey of the state of the art. *Security and Communication Networks*, pp.1-13.

Universal Robots. (2023, September 21). Types of Grippers Used in Manufacturing. Retrieved from https://www.universal-robots.com/blog/types-of-grippers-used-in-manufacturing/

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