Fabric materials classification device using YOLOv8 algorithm

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ABSTRACT

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The fashion industry in Indonesia significantly contributes to the country's creative economy. However, public knowledge about various types of fabric materials is still limited, often leading to fraud. This research aims to develop a device that can classify fabric materials based on their structure using computer vision techniques. The device uses a digital microscope endoscope magnifier 1600x USB camera to capture fabric structure images and the YOLOv8 algorithm to classify 17 types of fabric materials from 1,700 raw image data. The research methodology includes collecting fabric image datasets, preprocessing data, and training the YOLOv8 model. The results show that the YOLOv8 model achieves an accuracy of 98%. The classification results are displayed on an LCD connected to NodeMCU ESP8266. System testing shows that the device effectively classifies fabric materials, sends the results to the database via API, and displays the results on the LCD. Overall, this device provides an effective solution for distinguishing types of fabrics and preventing fraud in fabric purchases.

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INTRODUCTION 1.

Fashion in Indonesia is a leading subsector of the creative economy. This success is recognized and supported by the creative economy agency, which promotes the development of various models, accessories, and types of fabric materials. However, the general public's limited knowledge of the diverse types of fabric materials can lead to fraud by unscrupulous fabric or apparel sellers.

To prevent such fraud, a solution is needed to classify fabric materials accurately, allowing consumers to verify the authenticity of the fabric they intend to purchase. An effective solution should distinguish each type of fabric material precisely. Artificial intelligence (AI) [1], [2], with its ability to process and learn from vast amounts of data, provides a promising approach to this classification task [3].

Mori et al. [4] conducted a study to classify fabric materials based on color patterns using a machine learning approach with a forward propagation neural network algorithm. This research successfully distinguished three types of fabric materials: yukata, aloha shirt, and kariyushi shirt. However, the scope was limited to these three fabric types, making the results less applicable for broader use. The reliance on color patterns posed limitations since fabric materials often have unique structures that are not discernible through color patterns alone. Each type of fabric has a distinct structure requiring magnification to differentiate effectively. Oman et al. [5] addressed this by using a Canon IXUS 50 camera to capture images of fabric structures. They employed hierarchical cluster analysis (HCA) and principal component analysis (PCA) for classification. Despite their methodological rigor, their study focused on the subjective assessment of visual material preferences without specifying the semantic content of the fabric materials. This limited the practical applicability of their findings for broader fabric classification tasks.

Given the lack of comprehensive and objective solutions for fabric material classification, this research aims to develop a device that classifies clothing materials based on their structure. The study utilizes the YOLOv8 algorithm, known for its high accuracy in various classification tasks. Previous research demonstrates the algorithm's effectiveness in macro and micro-scale classifications, such as classifying cars running on the streets and classifying cells present in urine sediment samples.

Mudawi *et al.* [6] demonstrated the effectiveness of the YOLOv8 algorithm by classifying cars running on the streets into nine classes and eight classes using two datasets, each consisting of 6,000 images. The study achieved high accuracy results of 95.6% and 94.6%, respectively, showcasing the algorithm's capability to handle large datasets and complex classification tasks. Similarly, Akhtar *et al.* [7] used the YOLOv8 algorithm to classify cells present in urine sediment, achieving 91% accuracy in classifying 11 classes of urine particles. Luong *et al.* [8] also utilized the YOLOv8 algorithm to classify normal white blood cells and leukemia cells with an impressive accuracy of 95.1%.

The existing studies have notable limitations in classifying fabric materials. Mori *et al.* [4] focused on color patterns, which are insufficient for distinguishing fabrics with unique structures. Oman *et al.* [5] attempted structural analysis but relied on subjective assessments without clear semantic content. Although Akhtar *et al.* [7] and Luong *et al.* [8] effectively used the YOLOv8 algorithm for micro-scale tasks like cell classification, their methods were not applied to fabric materials. Mudawi *et al.* [6] demonstrated high accuracy in classifying cars, but this approach does not directly translate to fabric classification.

Due to these limitations, the author sees the need to develop a tool that accurately classifies 17 types of fabric materials based on their microscopic structures. This tool will utilize the YOLOv8 algorithm [9], [10] and a digital microscope endoscope camera magnifier 1600x USB to capture and analyze fabric images. By addressing the shortcomings of previous studies, this device aims to provide a reliable solution for fabric classification, helping consumers make informed decisions and reducing the risk of fraud in the fashion industry.

2. METHOD

This research focuses on classifying 17 fabrics, namely cotton, canvas, linen, denim, satin, silk, polyester, rayon, leather, suede, organza, jersey, nylon, jacquard, wool, spandex, and lace/brocade [11]-[14]. So, only 17 fabrics can be sampled; outside of that, it cannot be because the dataset entered only contains 17 types of fabric material.

Dataset retrieval is done with a microscope camera with 1600x magnification. Each type of fabric takes a photo of its structure at a certain magnification with a total of 100 photos for each type of fabric, so a total of 1,700 photos as a dataset. A dataset of 17 fabrics was taken with a camera microscope until the structure was visible, and the difference in structure for each type of fabric was shown.

From the dataset that has been made, there are differences in the structure of the 17 fabrics. This difference is learned by the YOLOv8 algorithm so that it can distinguish the 17 fabrics [15], [16]. After obtaining 1,700 images, this dataset was processed in several stages, as shown in Figure 1 to produce the best model for classifying 17 fabric materials.



Figure 1. Design stages of the YOLOv8 model

After obtaining the best model from processing by the YOLOv8 algorithm, this model is entered into the website so that when a photo of fabric material is loaded onto the website, the website can immediately perform classification and send the name of fabric materials that are being classified [17]-[19]. The stages until displaying the classification results can be seen in the Figure 2.



Figure 2. System block diagram designing

A program controls all of the above processes. There is a program for the classification and a program for the overall system. These two programs control every component. Each program has several stages until we get what we need from the program. The stages of the programs can be seen in Figure 3, with Figure 3(a) showing the classification program and Figure 3(b) showing the overall system program.



Figure 3. Program flowchart, (a) classification program flowchart and (b) overall system program flowchart

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The stages of the classification process begin with taking samples of fabric material with a microscope camera until the structure of the fabric material is visible then the image is loaded onto the website, and the classification program that has been embedded in the website will perform classification and publish the classification results to MQTT [20]-[22], then the ESP 8266 nodeMCU subscribes to MQTT classification results and displays the classification results on the LCD [23]-[25]. This stage is carried out by the hardware in the Figure 4.



Figure 4. Hardware system design

3. RESULTS AND DISCUSSION

3.1. Datasets

This research has created the dataset needed to get the best classification model, which is an image of the structure of 17 fabrics, with 100 images for each type of fabric and a total of 1,700 images obtained. Whereas none of the previous studies had images of fabric structure datasets. All images were taken at two magnifications with multiple fabrics of each fabric type. From the dataset images, we can see the different structures for each type of fabric. The examples of images obtained for 17 fabrics can be seen in Figure 5 in Appendix from a until q for each fabric material.

3.2. Best model

The classification model is varied on the YOLOv8 series and the number of epochs used with two magnification values of the microscope camera at sampling. All these variations are tried to see which variation has the best accuracy. There are five series in the YOLOv8 algorithm, but not all series are tried; only the series that has produced high accuracy. All experiments to get the best model can be seen in Table 1. From the Table 1, we found that the best model is YOLOv8 series m with epoch 25 at a magnification of 1400s-1500s. This model gets 98% accuracy, which is calculated by the confusion matrix as seen in Figure 6. There are four results of calculation values obtained from the program, namely the overall accuracy value of the model, precision value, recall, and F1-score for each type of fabric.

Table 1. Model trial							
YOLOv8 series	Epoch	Magnifier	Accuracy				
n	5	1400s-1500s	87%				
n	5	500s	61%				
n	25	1400s-1500s	89%				
n	25	500s	64%				
S	5	1400s-1500s	92%				
s	5	500s	66%				
S	25	1400s-1500s	93%				
s	25	500s	69%				
m	5	1400s-1500s	94%				
m	5	500s	71%				
m	25	1400s-1500s	98%				
m	25	500s	72%				

	precision	recall	f1-score
BROCADE	1.00	1.00	1.00
CANVAS	1.00	0.80	0.89
COTTON	1.00	1.00	1.00
DENIM	1.00	1.00	1.00
JACQUARD	1.00	1.00	1.00
JERSEY	1.00	1.00	1.00
LEATHER	0.83	1.00	0.91
LINEN	0.83	1.00	0.91
NYLON	1.00	1.00	1.00
ORGANZA	1.00	1.00	1.00
POLYESTER	1.00	1.00	1.00
RAYON	1.00	1.00	1.00
SATIN	1.00	1.00	1.00
SILK	1.00	1.00	1.00
SPANDEX	1.00	1.00	1.00
SUEDE	1.00	1.00	1.00
WOOL	1.00	0.80	0.89
accuracy			0.98

Figure 6. Model accuracy

The accuracy value above can be calculated using the confusion matrix formula, where these values can be taken from the confusion matrix results of the model testing results in Figure 7. The numbers are taken from sorting 17 types of fabric alphabetically from 0 to 16. For example, 0 is brocade fabric, 1 is canvas fabric, and then up to 16 is wool fabric.



Figure 7. Model test result data and confusion matrix

From the confusion matrix above, we can then calculate the accuracy value with the following formula [26]-[29]. The calculation precision, recall, and F1-score are not calculated manually in this paper because the precision, recall, and F1-score values exist in all types of fabric materials, while the accuracy value is only for the accuracy of the model, which is for all 17 types of fabric materials [30]-[32].

It can be seen that the results of manual accuracy calculations are the same as calculations made by the program, and the best model for classification is obtained with an accuracy of 98%. There is an error of 2% because there is an error in the prediction of fabric material number 1, namely canvas fabric, and number 16, namely wool fabric.

3.3. Classification test results

After getting the best model, classification can then be done. Classification testing is carried out on a mobile device with upload mode. Where the image of the fabric material is first taken and saved to the internal storage of the mobile device. Then, open the classification website and load the image of the fabric material to be classified. Perform classification until the classification results appear on the LCD, as shown in Figure 8 while Figure 8(a) shows the web display and Figure 8(b) shows the result on the device.

From the results obtained, we concluded that classifying fabric materials based on their structure is the best method to distinguish each fabric material, and this tool can be used to classify 17 fabric materials well. In contrast to previous studies that classify fabric materials based on color, which results in the same type of fabric material if the color is the same, this tool can classify 17 fabric materials even if the fabric color is the same. However, a 2% lack of accuracy is obtained from the dark color of the fabric material, so in the future, sufficient light is needed to classify fabric samples.



Figure 8. Classification result, (a) website display on a mobile device with the fabric image already loaded and (b) tool classification result display

4. CONCLUSION

From the results obtained, it can be concluded that a classification device has been made and can function appropriately in classifying 17 fabric materials. The results of the fabric materials classification were successfully sent to the database via API and displayed on the LCD. The best classification model is the YOLOv8 m series with epoch 25 with an accuracy of 98% and the best microscope camera magnification to classify fabric materials in the value range of 1400-1500s.

APPENDIX



Figure 5. Fabric materials dataset: (a) brocade, (b) canvas, (c) cotton, (d) denim, (e) jacquard, (f) denim, (g) leather, (h) linen, (i) nylon, (j) organza, (k) polyester, (l) rayon, (m) satin, (n) silk, (o) spandex, (p) suede, and (q) wool

Fabric materials classification device using YOLOv8 algorithm (Tuti Alawiya)

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	С	Μ	So	Va	Fo	Ι	R	D	0	Е	Vi	Su	Р	Fu
Tuti Alawiya		\checkmark	\checkmark		\checkmark	\checkmark	\checkmark	\checkmark	✓	\checkmark	✓		\checkmark	
Meqorry Yusfi				\checkmark	\checkmark	\checkmark				\checkmark		\checkmark	\checkmark	\checkmark
Muhammad Ridho Isdi	\checkmark	\checkmark	\checkmark					\checkmark		\checkmark	\checkmark			
Harmadi				\checkmark	\checkmark	\checkmark						\checkmark	\checkmark	

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : R esources	Su : Supervision
So : Software	D : Data Curation	P : P roject administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Meqorry Yusfi] and first author [Tuti Alawiya], upon reasonable request.

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