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Gender Identification and Population Detection in a Room Using YOLOv8

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Abstract *– In today's digital era, lectures and higher education have experienced rapid development, particularly in the use of technology. Technology has provided various opportunities to enhance efficiency and effectiveness in different aspects of education. One crucial aspect that requires improvement is student attendance tracking in lectures. This study aims to develop a system that addresses the issue of student attendance recapitulation by utilizing image processing technology and the YOLOv8 algorithm. Additionally, training data for male and female faces is incorporated to facilitate gender identification. By integrating modern technology with this innovative approach, the proposed system is expected to provide an efficient and accurate solution for recording student attendance in lectures. The results of this study indicate that the developed system successfully detects population numbers and identifies gender within a classroom. In this research, three consecutive tests using normal condition pollen images and YOLOv8l weights yielded a total precision value of 100%, a total recall value of 100%, and a total accuracy value of 100%.*

Keywords – *Image Processing; YOLOv8; Attendance System; Gender Identification; Deep Learning.*

I. Introduction

IN today's digital era, lectures and higher education have experienced rapid development, especially in the use of technology. Technology has opened up various opportunities to improve efficiency and effectiveness in various aspects of education. One of the aspects that need improvement is student attendance tracking in lectures.

Student attendance in lectures is an important indicator in assessing student participation in the educational process. However, many issues persist in student attendance recapitulation. A common problem is students attempting to manipulate attendance records through various means, such as proxy attendance where one student marks another absent student's presence. Automated attendance systems using biometric technologies like face recognition and RFID are being developed to address the issue of proxy attendance in educational settings [1, 2]. These systems aim to improve efficiency and accuracy over traditional manual methods [3]. Some approaches incorporate geofencing, dynamic QR codes, and IMEI checking to prevent fraud [4]. Machine learning algorithms are also being employed to detect anomalies in attendance patterns [5]. Smartphone-based solutions utilizing Wi-Fi fingerprinting and facial recognition have been proposed to reduce costs and hardware requirements [6]. Additionally, IoT-based systems using RFID and IR sensors can track student entry and exit, alerting teachers to discrepancies that may indicate proxy attendance [7]. These technological solutions aim to create more robust and reliable attendance monitoring systems [8].

To address this issue, a technological solution is required to provide an accurate and efficient system. One potential approach is image processing using a computer. In this case, computers can capture images of lecture halls and process them to detect student attendance. Automated attendance systems using facial recognition technology are gaining traction in educational settings, offering advantages over traditional manual methods [9, 10]. These systems typically involve capturing images or videos of classrooms, detecting faces using algorithms like Viola-Jones, and recognizing students through techniques such as LDA, HOG, or LBP [11, 12]. Machine learning classifiers like SVM, KNN, and neural networks are employed for

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face recognition [9, 12]. Continuous observation improves attendance estimation accuracy [10, 13]. These systems can operate in real-time, marking attendance automatically without disrupting lectures [14, 15]. Benefits include time-saving, improved accuracy, and the ability to generate attendance reports [16]. Overall, computer vision-based attendance systems offer an efficient solution to streamline attendance management in educational institutions.

This study aims to develop a system that resolves the issue of student attendance recapitulation by leveraging image processing technology and the YOLOv8 algorithm. Recent studies have explored automated student attendance systems using facial recognition and image processing technologies. Several papers propose using the YOLOv8 algorithm for face detection and recognition, achieving high accuracy rates [17–19]. These systems aim to replace traditional manual methods, which are time-consuming and prone to errors [20, 21]. Researchers have implemented various approaches, including one-shot learning [17], the Viola-Jones technique with LDA [20], and the YOLOv7 algorithm [22]. The proposed systems offer real-time monitoring, improved accuracy, and integration with web-based platforms for easy access and management [18, 23, 24]. These automated attendance systems promise to enhance efficiency, reduce fraud, and provide better resource allocation in educational settings. Furthermore, training data for male and female faces will be incorporated to facilitate gender identification. By integrating modern technology with this innovative approach, the proposed system is expected to offer an efficient and accurate solution for recording student attendance in lectures.

II. Research Methods

The research procedure is comprehensively illustrated in Figure 1, providing a clear visualization of the sequential steps involved in this study. The process begins with an extensive search and review of literature that is highly relevant to the research topic. This stage is crucial as it helps to establish a solid theoretical foundation and gain insights from previous studies. The gathered literature is thoroughly examined and analyzed to extract valuable information that can contribute to the understanding of the subject matter.

After acquiring sufficient background knowledge from various academic sources, the next step involves identifying specific problems that were encountered in previous research studies. This step ensures that the study is addressing existing gaps or limitations in the field, allowing for a more targeted and impactful investigation. By recognizing these unresolved issues, the research can focus on proposing improvements, modifications, or entirely new approaches to overcome the identified challenges.

Once the problems have been clearly defined, the next phase is determining the necessary system specifications required to effectively address these issues. This involves outlining the technical aspects, functional requirements, and design considerations that will shape the development of the system. If the available specifications are found to be inadequate, outdated, or ineffective in achieving the research objectives, an additional round of literature review is conducted. This iterative process ensures that the most suitable and optimized system specifications are formulated based on the latest technological advancements and research findings.

Following the specification refinement, the study proceeds to the system design phase, where the conceptual framework and structural layout of the proposed system are carefully developed. This stage plays a vital role in ensuring that all components work cohesively to achieve the intended objectives. Once the system design is completed, the research advances to the data testing phase, where experiments, simulations, or real-world testing are carried out to validate the system's functionality and effectiveness.

The collected data from the testing phase is then systematically analyzed using appropriate evaluation methods. Statistical tools, comparative analysis, and performance metrics may be employed to interpret the results accurately. Finally, based on the insights gained from the data analysis, well-founded conclusions are drawn regarding the system's overall efficiency, reliability, and potential for further improvements. The findings from this research contribute valuable knowledge to the field, providing a basis for future developments and applications.

i. Gender Dataset Labeling and Training

The stages for gender identification and population detection are illustrated in Figure 2. The gender dataset labeling and training process involves the following steps:

1. Collection of male and female face datasets. The dataset consists of 1528 male faces and 1379 female faces in JPG format, captured through cameras. The images are resized to 640x640 pixels.
2. Install library on Google Colab. Required libraries are installed in Google Colab to support the program.
3. Connecting Google Drive on Google Colab. Google Drive is linked to Google Colab to access the dataset images.
4. Unzip the dataset folder. The dataset ZIP file is

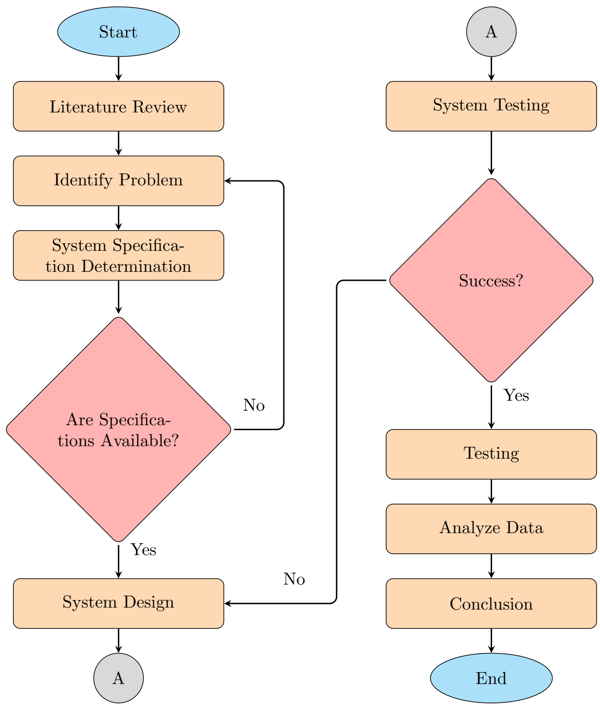


Figure 1: Flowchart of the Research Procedure.

extracted in Google Colab.

5. Resize dataset images. Images are resized to maintain input consistency, ensuring uniform dimensions for training.
6. Create a blank list. Two empty lists are created: one for storing image data and another for labels.
7. Label datasets. Labels are assigned to the dataset for classification.
8. Split training and testing datasets. The dataset is divided, with 20% allocated for testing.
9. Add augmentation data. Augmentation techniques are applied to generate variations of training images.
10. Train gender dataset model. The dataset is trained to recognize gender based on the assigned labels.
11. Save the trained model. The trained model is stored in Google Drive for future use.

ii. *Face Detection and Gender Identification Training*

The process for face detection and gender identification training is illustrated in Figure 3. The procedure involves:

1. Cloning the YOLOv8 GitHub repository to Google Colab.
2. Importing the face dataset from Roboflow.
3. Training the YOLOv8 model for face detection in Google Colab.
4. Downloading the gender identification model in Google Colab.
5. Downloading the `predict.py` script in Google Colab.
6. Running the script `!python.py model='best.pt' source '.jpg'` to identify gender and detect population count in a room. The output is then displayed.

iii. *Camera Placement Plan*

The camera placement is designed to ensure accurate face detection. The camera is positioned in the center of a 3×3 meter room, facing the objects to be detected, as illustrated in Figure 4.

iv. *User Interface*

The user interface, shown in Figure 5, functions as follows:

1. Capture a detection image using the camera.
2. Save the image on the device.
3. Insert the image into the program on Google Colab.
4. Run the program on Google Colab by executing `Runtime`.
5. The output consists of a processed image displaying gender information and the population count.

v. *Population and Sample*

Population refers to the number of inhabitants, including humans and other living organisms within a certain area [25]. In humans, population dynamics are influenced by factors such as birth and death rates. The concept of population is categorized into two scopes:

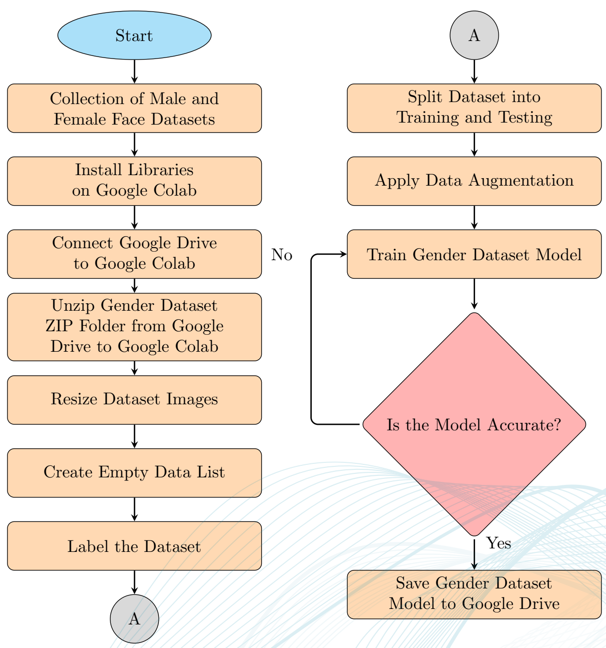


Figure 2: Gender Dataset Labeling and Model Training.

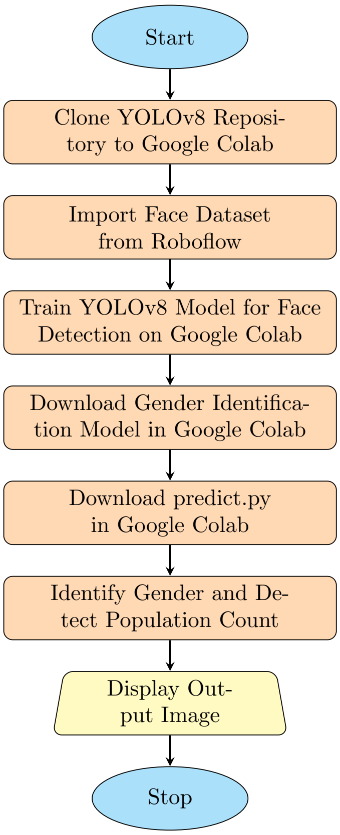


Figure 3: Face Detection and Gender Identification Training.

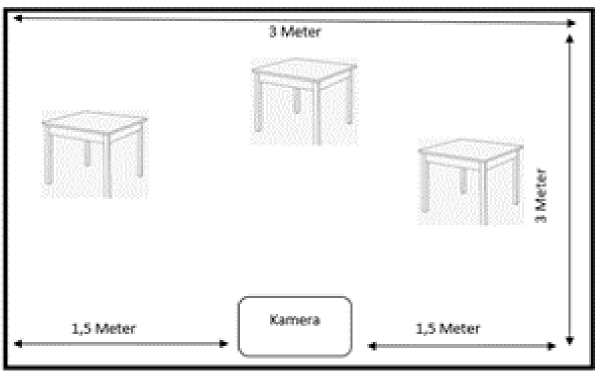


Figure 4: Camera Placement Plan.

the biological scope, which involves birth, growth, differentiation into old age, and death; and the statistical scope, which is influenced by birth and death rates.

vi. Artificial Intelligence (AI) in Computer Vision

Artificial Intelligence (AI) is intelligence integrated into a system to perform specific functions and tasks, enabling the system to interpret data as either true or false based on learning from previous data [26]. AI is designed to automate tasks and produce results similar to those performed by humans.

vii. YOLO

You Only Look Once (YOLO) is an algorithm used for real-time object detection. The detection system repurposes classifiers or localizers to detect objects by applying a model to an image at multiple locations and scales. The region with the highest confidence score is identified as a detection [27]. YOLO employs artificial neural networks (ANN) to detect objects within an image. The network segments the image into multiple regions and predicts bounding boxes and confidence scores for each region. These predictions are then evaluated to identify the most probable object locations.

To assess the quality of a YOLO model, training and validation results are typically evaluated using various scoring metrics. Several key parameters are commonly used for performance evaluation in YOLO training.

viii. Confusion Matrix

A confusion matrix is a table that illustrates the performance of a classification model by comparing predicted classifications with actual outcomes. From this matrix, evaluation metrics such as accuracy, precision, and F-score can be computed based on the classified data conditions [28]. Figure 6 presents the standard confusion matrix.

The elements of the confusion matrix include:

1. `True Positive (TP)`: The model correctly classifies data as positive.
2. `True Negative (TN)`: The model correctly classifies data as negative.
3. `False Positive (FP)`: The model incorrectly classifies negative data as positive.
4. `False Negative (FN)`: The model incorrectly classifies positive data as negative.

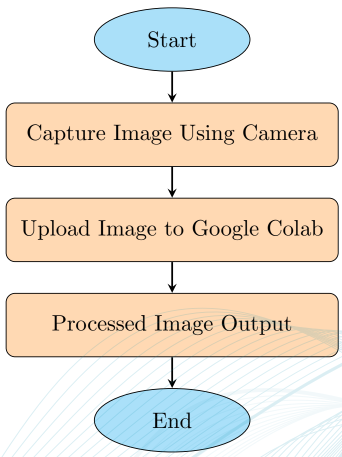


Figure 5: User Interface for Face Detection and Gender Identification.

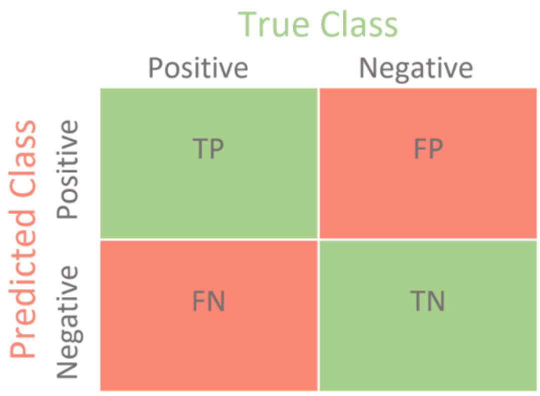


Figure 6: Confusion Matrix [28].

ix. Accuracy

Accuracy measures how well the model correctly classifies the overall dataset. It is computed using Equation (1):

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

x. Precision

Precision evaluates the proportion of true positive classifications relative to all instances classified as positive. It is given by Equation (2):

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

xi. Recall

Recall assesses the proportion of correctly classified positive instances relative to all actual positive cases. It is computed using Equation (3):

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

xii. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a powerful and widely used deep learning model, specifically designed for computer vision applications. This type of artificial neural network is highly effective in processing visual data due to its ability to automatically learn spatial hierarchies of features through multiple layers of convolutional operations. Unlike traditional machine learning models that rely heavily on manual feature extraction, CNNs are capable of identifying complex patterns, textures, and structures within images by leveraging their deep, multilayered architecture.

CNNs consist of several essential components, including convolutional layers, activation functions, pooling layers, and fully connected layers. The convolutional layers apply filters to extract key features from input images, such as edges, corners, and textures, while the activation functions, such as ReLU (Rectified Linear Unit), introduce non-linearity to enhance learning capabilities. The pooling layers, typically max pooling or average pooling, reduce the spatial dimensions of the extracted features, improving computational efficiency and reducing overfitting. Finally, the fully connected layers compile the learned features to make final predictions, classifying objects or detecting patterns within the input data [29].

Due to their hierarchical feature extraction process, CNNs excel in a wide range of computer vision tasks, including image classification, object detection, facial recognition, and image segmentation. In image classification, CNNs categorize images into predefined labels, such as identifying handwritten digits or distinguishing between different species of animals. Object detection involves locating and identifying multiple objects within an image, often using models like YOLO (You Only Look Once) or Faster R-CNN. Facial recognition utilizes CNNs to match facial features with stored data for identity verification, playing a crucial role in security and biometric applications. Additionally, in image segmentation, CNNs assign pixel-level labels to an image, which is essential for medical imaging, autonomous driving, and other high-precision tasks.

The adaptability and efficiency of CNNs make them indispensable in modern artificial intelligence and deep learning applications, with ongoing advancements continuously improving their accuracy and performance in real-world scenarios.

III. Results and Discussion

i. Dataset

In this study, two different datasets were used. The first dataset consists of facial images, while the second dataset comprises male and female facial images obtained from Roboflow and the internet in Joint Photographic Group (JPG) format. These datasets are used for machine training.

Table 1: Distribution of Facial Image Data

Data Type	Count
Train	2,871
Validation	267
Test	3
TOTAL	3,283

Based on Table 1, the training and validation datasets are labeled according to the class type for model training purposes. Meanwhile, the test dataset remains unlabeled to assess the detection accuracy of the trained model. This dataset is essential for measuring model performance and ensuring that the model can predict accurate results.

Table 2: Distribution of Male and Female Facial Image Data

Gender	Number of Datasets
Male	1,528
Female	1,379

This facial dataset is classified into two categories: male and female, as presented in Table 2. Each image has dimensions of $100 \times 100 \times 3$ pixels, which ensures consistency in input size for effective machine learning model training.

The test results were carried out using the weights stored from the training results of the YOLO V8l model, which was trained for 80 Epochs. This test was conducted in a room environment, where images were taken using an OPPO RENO 4F smartphone camera with a 48 MP resolution. The test was performed on three different images from different rooms, analyzing the gender identification and population detection results in the tested images.

ii. Identification and Detection in Room 1

(a) Actual Conditions

(b) YOLOV8 Prediction Conditions

Figure 7: Results of Gender Identification and Detection of Population Number in Room 1.

Based on Figure 7, the results of gender identification and population detection in Room 1 indicate that YOLOV8 successfully detected 7 faces, identifying 5 males and 2 females. Table 3 presents the comparison between the actual condition and the YOLOV8 predicted values.

Table 3: Comparison of Gender Identification with Actual and Predicted Values in Room 1.

Gender	Actual Count	YOLOV8 Prediction
Male	5	5
Female	2	2

Based on Table 3, the precision, recall, and accuracy values are calculated as follows:

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{5}{5+0} = 1 = 100\% \quad (4)$$

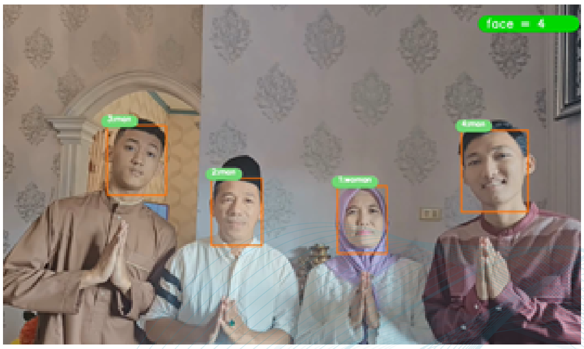
$$\text{Recall} = \frac{TP}{TP+FN} = \frac{5}{5+0} = 1 = 100\% \quad (5)$$

$$\begin{aligned} \text{Accuracy} &= \frac{TP+TN}{TP+FP+TN+FN} \\ &= \frac{5+2}{5+0+2+0} = 1 = 100\% \end{aligned} \quad (6)$$

The results indicate 100% accuracy, precision, and recall, meaning that YOLOV8 performed perfectly in detecting gender and population numbers in Room 1.

iii. Identification Detection in Room 2

(a) Actual Conditions



(b) YOLOV8 Prediction Conditions

Figure 8: Results of Gender Identification and Detection of Population Number in Room 2.

Based on Figure 8, the results of gender identification and population detection in Room 2 indicate that YOLOV8 successfully detected 4 faces, identifying 3 males and 1 female. Table 4 presents the comparison between the actual condition and the YOLOV8 predicted values.

Table 4: Comparison of Gender Identification with Actual and Predicted Values in Room 2.

Gender	Actual Count	YOLOV8 Prediction
Male	3	3
Female	1	1

Table 5: Comparison of Gender Identification with Actual and Predicted Values in Room 3.

Gender	Actual Count	YOLOV8 Prediction
Male	20	20
Female	0	0

Based on Table 4, the precision, recall, and accuracy values are calculated as follows:

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{3}{3+0} = 1 = 100\% \quad (7)$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{3}{3+0} = 1 = 100\% \quad (8)$$

$$\begin{aligned}\text{Accuracy} &= \frac{TP+TN}{TP+FP+TN+FN} \\ &= \frac{3+1}{3+0+1+0} = 1 = 100\%\end{aligned} \quad (9)$$

The results indicate 100% accuracy, precision, and recall, meaning that YOLOV8 performed perfectly in detecting gender and population numbers in Room 2.

iv. Identification and Detection in the 3rd Room

Based on Figure 9, the results of gender identification and population detection in Room 3 indicate that YOLOV8 successfully detected 20 faces, identifying 20 males and 0 females. Table 5 presents the comparison between the actual condition and the YOLOV8 predicted values.

Based on Table 5, the precision, recall, and accuracy values are calculated as follows:

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{20}{20+0} = 1 = 100\% \quad (10)$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{20}{20+0} = 1 = 100\% \quad (11)$$

(a) Actual Conditions

(b) YOLOV8 Prediction Conditions

Figure 9: Results of Gender Identification and Population Number Detection in Room 3.

Table 6: Precision, Recall, and Accuracy for All Three Tests.

Testing	Precision (%)	Recall (%)	Accuracy (%)
First Test	100	100	100
Second Test	100	100	100
Third Test	100	100	100
Average (%)	100	100	100

$$\begin{aligned}\text{Accuracy} &= \frac{TP+TN}{TP+FP+TN+FN} \\ &= \frac{20+0}{20+0+0+0} = 1 = 100\%\end{aligned} \quad (12)$$

v. Average Precision, Recall, and Accuracy

$$\text{Total Precision} = \frac{1+1+1}{3} = 1 = 100\% \quad (13)$$

$$\text{Total Recall} = \frac{1+1+1}{3} = 1 = 100\% \quad (14)$$

$$\text{Total Accuracy} = \frac{1+1+1}{3} = 1 = 100\% \quad (15)$$

The results in Table 7 confirm that YOLOV8 achieved a 100% success rate in detecting the population numbers accurately in all three test cases.

Table 7: Comparison of Population Detection with Actual Values and YOLOV8 Prediction Conditions.

Testing	Actual Count	YOLOV8 Prediction
First Test	7	7
Second Test	4	4
Third Test	20	20

IV. Conclusion

The conclusion of this study is that this system successfully detects the number of people and identifies gender in a given room. Across all test cases, using the YOLOV8 algorithm, the results show a total precision, recall, and accuracy of 100%.

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