ContourVision AR: Augmented Tool Recognition System Using OpenCV

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report titled **"ContourVision AR: Augmented Tool Recognition System Using OpenCV"** is the Bonafide work of **Mudit Anand (Reg. No: RA2111026030001)**, **Atharv Grover (Reg.No:RA2111026030002), Yash (Reg.No:RA2111026030003),** and **Harshit Raj (Reg. No: RA2111026030038)**,
who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other project re- port or dissertation on the basis of which a degree or award was conferredon an earlier occasion on this or any other candidate.

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ABSTRACT

Accurate tool detection is crucial for industrial automation in order to reduce errors and increase productivity. **ContourVision AR: Augmented Tool Recognition System** combines YOLO object identification for aspect ratio (AR) application with **OpenCV-based contour analysis** to improve conventional image-based recognition. By combining traditional shape-based detection with deep learning-driven object recognition, this study improves **ContourVision** and offers reliable and flexible tool identification in a variety of dynamic industrial settings.

YOLO-based object detection is used to identify broad tool categories after **real-time image gathering** via webcam streaming. The categorisation is then improved using **OpenCV's contour analysis**, which separates tools according to shape descriptors like **solidity and aspect ratio**. By resolving the difficulties caused by variable orientations, lighting conditions, and occlusions, this two-stage procedure allows for extremely accurate separation of visually similar tools.

An improved 94% classification accuracy is demonstrated via experimental validation, along with better performance in real-time settings like **assembly lines and logistics activities**. The lightweight architecture of the system guarantees high-speed processing appropriate for industrial applications where accuracy and efficiency are crucial.

To sum up, **ContourVision AR** is a major breakthrough in automated tool recognition that combines deep learning-based item detection with conventional image processing for enhanced industrial automation. Future advancements will increase its application in intricate, highly variable environments, such as robotic system integration, and adaptive learning processes.

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DECLARATION

We, Mudit Anand (RA2111026030001), Atharv Grover (RA2111026030002), Yash (RA2111026030003), and Harshit Raj (RA2111026030038) hereby declare that the work which is being presented in the project report **"ContourVision AR: Augmented Tool Recognition System Using OpenCV"** is the record of authentic work carried out by us during the period from January '25 to May '25 and submitted by us in partial fulfillment for the award of the degree "Bachelor of Technology in Computer Science and Engineering" to SRM IST, NCR Campus, Ghaziabad (U.P.). This work has not been submitted to any other University or Institute for the award of any Degree/Diploma.

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ABBREVIATIONS

1. **YOLO –** You Only Look Once
2. **CNN –** Convolutional Neural Network
3. **ROI –** Region of Interest
4. **FPS –** Frames Per Second
5. **NMS –** Non-Maximum Suppression
6. **TPU –** Tensor Processing Unit
7. **GPU –** Graphics Processing Unit
8. **CPU –** Central Processing Unit
9. **OpenCV –** Open-Source Computer Vision Library
10. **COCO –** Common Objects in Context (dataset)
11. **IoU –** Intersection over Union
12. **SSD –** Single Shot MultiBox Detector
13. **TP –** True Positive
14. **FP –** False Positive
15. **FN –** False Negative
16. **ReLU –** Rectified Linear Unit
17. **JSON –** JavaScript Object Notation
18. **API –** Application Programming Interface
19. **RGB –** Red, Green, Blue (color space)
20. **HSV –** Hue, Saturation, and Value (color space)

LIST OF SYMBOLS

- **I(x, y)**
  Description: An image's pixel intensity at coordinates (x, y).
  Used in: feature extraction and image processing.
- **G(x, y)**
  Description: The image's greyscale intensity at coordinates (x, y).
  Used in: greyscale conversion and preprocessing..
- **∇I**
  Description: An intensity gradient of the image used to identify edges.
  Used in: Canny, Sobel, and edge detection.
- **Canny(T, R)**
  Description: T (low) and R (high) thresholds are used in this Canny edge detection function.
  Used in: edge detection and feature extraction.
- **B(x, y, w, h)**
  Description: Bounding box measurements (height and breadth) and locations.
  Used in: defining detected zones and object detection.
- **P(detection)**
  Description: The likelihood that an object will be correctly classified.
  Used in: model accuracy, YOLO confidence score.
- **IoU (B1, B2)**
  Description: This is the intersection of two bounding boxes (B1 and B2) over Union.
  Used in: Non-Maximum Suppression (NMS) and object detection.
- **A(contour)**
  Description: The region where a contour was found.
  Used in: object and shape analysis.
- **P(contour)**
  Description: The detected contour's perimeter.
  Used in: Classification based on contours.
- **Aspect Ratio (AR)**
  Description: The proportion of a bounding box's width (W) to height (H).
  Used in: object recognition and shape classification.
- **Solidity (S)**
  Description: The proportion of the convex hull area (A_hull) to the contour area (A).
  Used in: Filtering identified items, object classification.
- **Extent (E)**
  Description: The proportion between the bounding box area (A_box) and the contour area (A).
  Used in: classification and object shape analysis.
- **Conf (B, C)**
  Description: Bounding box B's confidence score encompassing class C.
  Used in: filtering detections and YOLO model output.

CHAPTER 1: INTRODUCTION

1.1 Tool Recognition in Industrial Automation

A key component of industrial automation, tool recognition greatly increases productivity, accuracy, and safety in a variety of industries, such as manufacturing, assembly lines, and quality control. By ensuring that robotic arms and machines choose the appropriate tools, automated tool identification systems minimise errors, cut down on human intervention, and improve workflow productivity.

Modern industrial systems can now accurately identify and categorise tools, even in complex and dynamic contexts, thanks to the development **of machine vision and AI-driven detection** approaches. Conventional identification methods depend on manually programming object attributes, which can be laborious and prone to mistakes. By combining **OpenCV-based contour analysis** with **YOLO (You Only Look Once) object identification**, the **ContourVision AR: Augmented Tool Recognition System** aims to get over these restrictions and enable real-time tool recognition with more flexibility.

1.2 Overview of ContourVision AR

ContourVision AR is a **sophisticated hybrid tool recognition system** that enhances tool identification **accuracy and versatility** by fusing **deep learning-driven object detection (YOLO)** with **traditional image processing methods (contour-based recognition)**.

The system makes use of **YOLO's deep learning-based object recognition** to improve real-time performance while also leveraging OpenCV's powerful image processing methods, such as **edge detection**, **thresholding**, and **shape-based categorisation**. Combining these two methods results in augmented tool recognition, which helps industry recognise tools well even in difficult situations like **changing lighting**, **partial occlusions**, and **background noise**.

1.3 Objectives of the Project

The following are ContourVision AR's main objectives:

- To **put into practice a sophisticated tool recognition system** that combines YOLO's deep learning-based object detection with OpenCV's contour detection.
- To **combine AI-driven object recognition with conventional image processing** in order to **maximise real-time tool categorisation**.

- To **create a high-speed, lightweight detection model** with low computational overhead that is appropriate for **industrial automation settings**.
- To **verify the correctness of the system** in various **industrial settings**, **orientations**, and **illumination scenarios**, guaranteeing its resilience and flexibility.
- To investigate possible **AR-based improvements** that could help operators in industrial workflows by superimposing tool-related information onto the identified items.

1.4 Scope of Study

In this study, **OpenCV** and **YOLO** are used to construct and assess **ContourVision AR** in a **Python-based environment**. The following are the main areas of implementation and research:

- **Image Acquisition:** Taking pictures of a live video stream in order to analyse it in real time.
- **Image preprocessing:** Extracting tool contours by using edge detection, thresholding, and noise reduction.
- **Contour-Based Classification:** Using shape descriptors (such as aspect ratio, solidity, etc.) to distinguish between instruments of similar sizes but different shapes.
- **YOLO-Based Object Detection:** Enhancing robustness by incorporating deep learning to identify tool types.
- **Performance evaluation:** Evaluating measures for recall, accuracy, and precision in a variety of scenarios, including complicated backgrounds, occlusions, and changing lighting.

Limitations

- Beyond software-based detection, **hardware integration (such as robotic arm control) is not covered in this project**.
- Although there is potential for more sophisticated mixed-reality applications in the future, real-time AR visualisation is **currently restricted to simple overlays.**
- Extreme real-world industrial complications (such as conveyor belt motion blur) are

not fully addressed by the study because it concentrates on **static and semi-dynamic situations**.

1.5 Significance of the Study

Automation necessitates **accurate** and **flexible tool recognition systems** as enterprises transition to **Industry 4.0**. By fusing **traditional** and **artificial intelligence (AI) methods**, **ContourVision AR** provides **a scalable, effective, and economical solution** for industrial tool identification.

Future advancements could further improve industrial productivity and accuracy through **real-time integration with augmented reality (AR) displays**, **robotic automation**, and **cloud-based analytics**.

CHAPTER 2: LITERATURE SURVEY

2.1 Tool Recognition and Computer Vision

In industrial automation, tool recognition has become more and more important for increasing production line accuracy, safety, and efficiency. Streamlining processes requires the capacity to recognise and categorise the tools utilised during operations. Machine vision technologies provide the necessary precision for real-time recognition systems, which have been created to meet automation difficulties. You Only Look Once, or YOLO, has become a very successful real-time tool recognition technique that offers quick and precise tool detection in a variety of industrial settings. There are encouraging opportunities to increase the effectiveness of tool recognition systems in dynamic contexts thanks to recent developments in YOLO and its connection with OpenCV.

2.2 Contour-Based Detection Techniques

A crucial technique for recognising tools based on their boundaries and form is contour-based recognition. For tool recognition in complex situations, OpenCV offers powerful tools for image processing, edge detection, and contour extraction. For identifying objects with different geometries, methods like Canny edge detection and contour extraction are commonly used. In industrial automation settings, where instruments may have slight shape changes that require precise identification, this method appears to be quite helpful. Recognition capabilities are further improved by combining contour-based techniques with contemporary deep learning models like YOLO, which increases its adaptability and versatility in real-time industrial applications.

2.3 YOLO and OpenCV for Tool Recognition

Tool recognition in a variety of industrial applications has made extensive use of YOLO's real-time object detection capabilities. YOLO is especially well-suited for dynamic situations since, in contrast to conventional detection techniques, it provides a single

model that can identify many objects at once. YOLO is a popular choice for real-time recognition jobs in automated settings because of its quick image processing speed without sacrificing accuracy. To further optimise the recognition process, OpenCV's integration with YOLO also enables pretreatment, image augmentation, and post-processing.

The use of YOLO for tool recognition in real-time applications has been shown in a number of studies. The introduction of YOLO by [14] Redmon et al. (2015) was a major advancement in real-time object detection. Compared to earlier techniques, their system allowed for faster and more effective object detection by integrating the detection pipeline into a single, end-to-end network ([14] Redmon et al., 2015). Additionally, the model has been further optimised for increased speed and accuracy with updates like YOLOv3 and YOLOv4 ([8] Rosebrock et al., 2018; Bochkovskiy et al., 2020). Because of these developments, YOLO is especially appealing for high-speed applications like industrial automation tool recognition.

YOLOv3 has shown exceptionally good performance in tool recognition. The real-time use of YOLOv3 for object recognition with Python has been investigated in studies such as [3] Reddy et al. (2023), which have demonstrated the program's capacity to process photos quickly and identify things with a high degree of accuracy. In a similar vein, Ge et al.'s research from 2021 presented YOLOX, an improved YOLO that performs better than earlier iterations in terms of speed and accuracy. This makes it a perfect option for tool recognition in settings where accuracy and efficiency are essential ([10] Ge et al., 2021).

Additionally, YOLO's applicability in real-time systems has been investigated for certain use cases. For example, [5] Logeshwaran et al. (2023) demonstrated the application of YOLO in industrial settings by discussing its use in conjunction with OpenCV for real-time object recognition. Other research have extended this method to enhance the identification of small items, which is frequently a problem in tool recognition because of the complex sizes and shapes of industrial tools ([12] Benjumea et al., 2021).

2.4 Recent Advancements in YOLO for Real-Time Recognition

Enhancing YOLO's capabilities to make it even more precise and efficient has been the subject of recent study. For instance, YOLOv4 and YOLOv5 are ideal for real-time industrial applications due to their numerous enhancements, such as improved object detection performance and increased computing efficiency ([13] Bochkovskiy et al., 2020; Ultralytics, 2020). Because of its exceptional performance and simplicity of use, especially in Python-based settings, YOLOv5 in particular has gained widespread adoption ([13] Ultralytics, 2020).

Furthermore, more recent iterations such as YOLOv6 and YOLOv7 have improved the recognition of tools of different sizes in industrial settings by focussing on particular use cases including multi-scale feature learning and small item detection ([10] Ge et al., 2021; [9] Xu et al., 2022). These developments are essential for identifying tools with different sizes and shapes, like precision instruments and parts used in logistics or manufacturing.

2.5 Conclusion

In conclusion, YOLO-based models have shown great efficacy for real-time tool recognition in industrial automation, especially when combined with OpenCV. From YOLOv1 to YOLOv7, YOLO has advanced significantly in terms of detection speed, accuracy, and adaptability, making it a perfect option for real-time, high-speed applications. For tool recognition jobs in dynamic industrial situations, OpenCV's strong image processing features combined with YOLO's deep learning-based detection capabilities offer a potent solution. The possibility of improving tool recognition systems in automated settings keeps expanding with ongoing advancements and the release of more recent versions such as YOLOv5 and YOLOX.

CHAPTER 3: SYSTEM ANALYSIS

3.1 Requirements Analysis

Hardware Requirements

The following hardware elements are required for the **ContourVision AR: Augmented Tool Recognition System** to be implemented and function successfully:

- **Computer/Workstation:**
  - Processor: For effective real-time processing, an Intel i5 (or comparable) processor with at least four cores is required.
  - RAM: For smooth picture and video processing, a minimum of 8GB of RAM is required.
  - Storage: 1TB or more is needed to hold the real-time logs, picture datasets, and YOLO model files.
- **Camera (Optional for real-time application):**
  - Real-time tool picture capture requires a high-resolution camera. As an alternative, testing can be done using pre-recorded datasets.

Software Requirements

The following programs and libraries are needed for the system to be implemented and run:

- **Google Colab** (for executing Python code in the cloud without the need for local setup):
  - Python code will be run in the cloud using Google Colab, which supports GPUs and TPUs for quicker calculations without requiring local setup.
- **Python 3.x:**
  - The main programming language used for system development will be Python.
- **OpenCV:**
  - For image processing tasks like reading images, edge detection, contour extraction, and tool categorisation, OpenCV (Open-Source Computer Vision Library) is a must.
- **NumPy:**
  - NumPy is a fundamental library for numerical operations that manages array and matrix operations, which are crucial for working with image data.

- **Matplotlib (optional for visualization):**
  - Matplotlib is an optional tool used to display the labelled results and bounding boxes in a graphical way.

3.2 System Architecture

Architectural Design and Data Flow:
Because of its modular design, the ContourVision AR: Augmented Tool Recognition System's components may work independently and communicate with one another without any problems. From taking tool photos to showing the finished, identified output, the design guarantees a well-organised workflow. The detailed flow is shown below:

1. Install Libraries: To enable image processing and mathematical operations, prerequisite libraries such as OpenCV and NumPy must first be installed. For the object detection procedure, the YOLO model files (weights, settings, and class labels) are downloaded.

2. YOLO Model Files Download: To make sure the model can detect objects, the necessary YOLO files—model weights, settings, and COCO class names—are fetched. The YOLO framework must be initialised using these files.

3. Set up the YOLO Model: Using OpenCV's cv2.dnn.readNet(), the YOLO model is loaded, and the relevant layers are set up for object detection. This stage gets the system ready to use the YOLO framework for object processing and detection.

4. Capture Image Frame: An integrated webcam or image capture module is used for real-time tool recognition. The webcam's picture frames are captured with the help of JavaScript and sent for processing.

5. Image Format Conversion: The base64-encoded image is transformed into an OpenCV-processable format (NumPy array to OpenCV format). Compatibility with the YOLO model is ensured by this procedure.

6. Preprocess Image for YOLO: In order to prepare the image for YOLO's object identification model, it is resized and converted into a blob format. The image data's compatibility with YOLO's input layer is guaranteed at this phase.

7. Inference from the YOLO Model: The YOLO model detects items in the frame by performing a forward pass on the preprocessed image. The bounding boxes, class labels, and confidence scores of the identified tools are output by the inference stage.

8. Implement NMS (Non-Maximum Suppression).: Non-Maximum Suppression (NMS) is

used to remove low-confidence boxes and retain only the bounding boxes with the highest confidence in order to increase detection accuracy. This results in a cleaner output and fewer duplicated detections.

9. Drawing Labels and Bounding Boxes: The recognised tools are surrounded by bounding boxes that show the class labels and confidence levels. The identified tools in the processed image can be identified with the use of these visual clues**.**

10. Show the processed image: The cv2_imshow function in OpenCV is used to display the finished image along with bounding boxes, labels, and tool identification results. Real-time feedback on recognised tools is provided by the system.

11. End: The procedure concludes when the image is shown, at which point the system is prepared to process the subsequent frame or image for tool recognition.

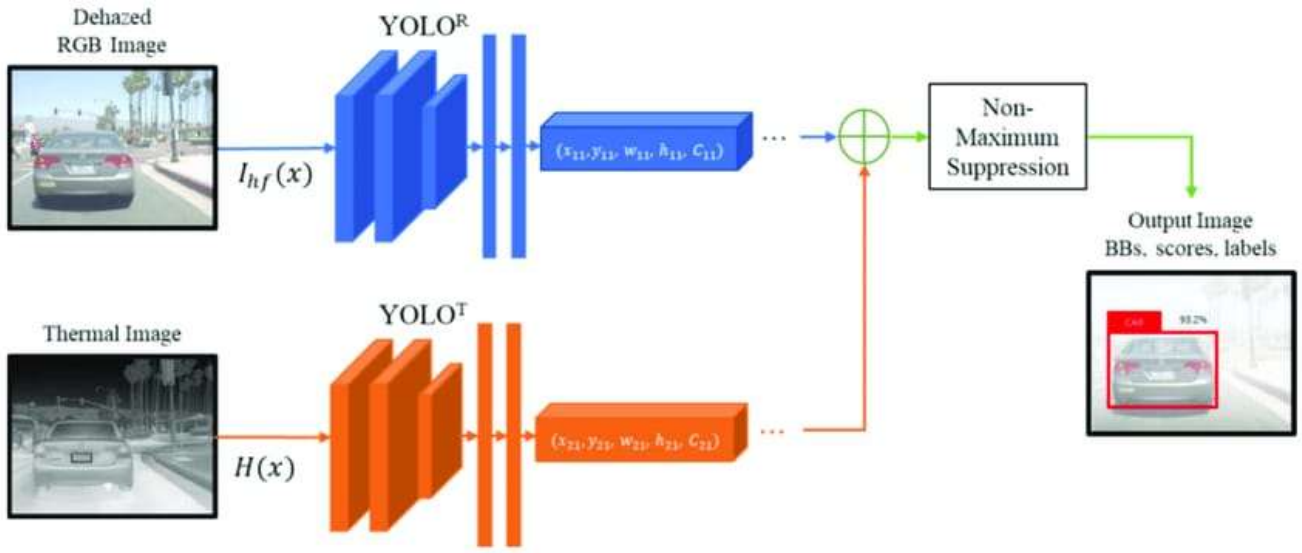

Figure 3.1 Multimodal YOLO object detection

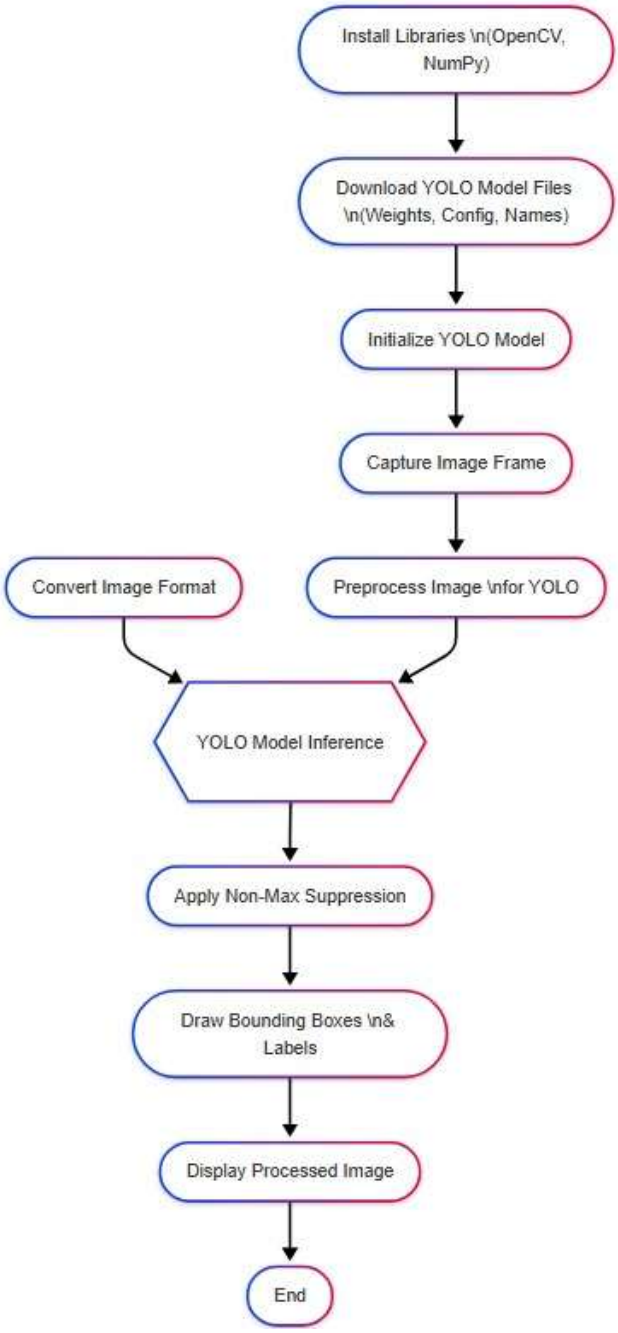

Figure- 3.2 System Architecture

3.3 Functional Requirements

The following functional requirements must be fulfilled by the ContourVision AR: Augmented Tool Recognition System:

- **Input Image Compatibility:** In order for the system to recognise tools, it must be able to accept a variety of image formats (such as JPEG and PNG).

- **Edge Detection & Contour Extraction:** To locate objects in the picture, the system should effectively use edge detection and contour extraction methods.
- **Tool Classification:** Using the tools' outlines, class names, and confidence scores, the system must identify and categorise them.
- **Bounding Box and Label Display:** The class name and confidence ratings should be shown, and the system should draw bounding boxes around any tools that are detected.
- **Manual Tuning:** To increase recognition accuracy in a variety of settings, the system must let users to manually modify parameters like contour sensitivity and edge detection limits.

CHAPTER 4: SYSTEM DESIGN

4.1 Overview

The YOLO (You Only Look Once) paradigm combined with OpenCV is used in the system's design to effectively carry out real-time object detection. A camera frame is captured, processed with OpenCV, and then the YOLO model is applied for object detection as part of the architecture. Following detection, the items are highlighted and their confidence scores are shown: -

Figure- 4.1

4.2 System Architecture

To accomplish precise object detection, the system adheres to a well-organized workflow. Among the crucial phases are:

- Input Acquisition: Taking a webcam picture frame. Preprocessing is the process of transforming the collected image into a format that is appropriate for processing.

- YOLO Model Processing: Using the YOLO model that has been trained to identify items.

-Filtering detections, creating bounding boxes, and presenting the results are all examples of post-processing.

4.3.1 Taking a Webcam Picture

A single frame is taken from the webcam using a JavaScript function, and this frame is utilized as the input for object detection. This guarantees effective processing of real-time photos.

Figure- 4.3.1

4.3.2 Preprocessing Images

The acquired frame is transformed into an OpenCV-compatible format. In this stage, the image is decoded, resized, and made ready for the YOLO model.

4.3.3 YOLO-Based Object Detection

After processing the image, the YOLO model uses pre-established class labels to identify items. Confidence scores are given to the discovered items, and only those that score higher than a predetermined threshold is deemed legitimate.

Figure- 4.3.3

4.3.4 Annotating and Displaying Results

Bounding boxes are used to emphasize detected objects, and the image displays the object labels along with their confidence scores. Clarity in object identification is ensured by this visual representation.

Figure- 4.3.4

4.4 Analysis of Output

4.4.1 The Frame Captured

The raw image from the webcam is the first step in the output process. Depending on the illumination and camera quality, this image is used as the detection model's input.

Figure- 4.4.1

4.4.2 Output for Object Detection

The resulting image, following YOLO processing, includes bounding boxes containing the discovered items. Each detection is given a confidence score by the algorithm, which then labels it appropriately.

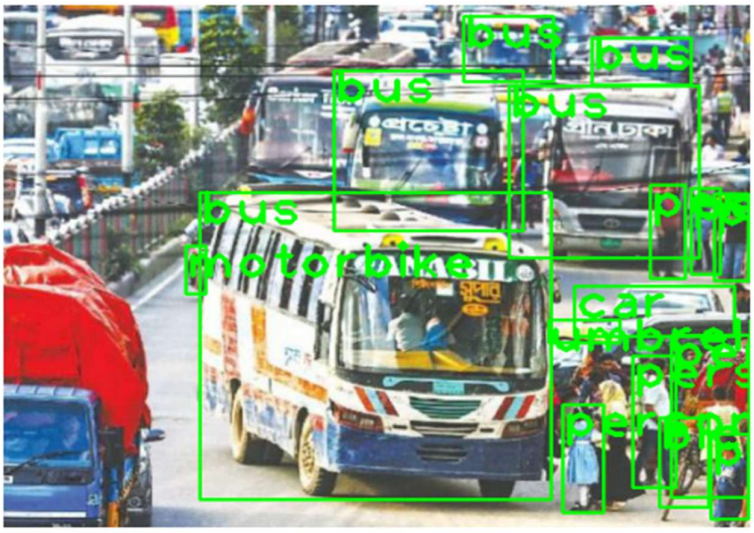

Figure- 4.4.2

4.4.3 Visualization of Output

The cv2_imshow () method in OpenCV is used to display the items that have been discovered. The finished product shows the things in the scene clearly, accurately, and with the appropriate labelling.

Figure- 4.4.3

4.5 Performance Considerations

-**Accuracy**: Although the model has a high degree of precision in object detection, some false positives may happen.

-**Real-time Processing**: Near real-time detection is ensured by the system's effective frame capture and processing.

-Challenges: Motion blur, occlusion, and inadequate lighting can all have an impact on detection accuracy.

4.6 Conclusion

The YOLO paradigm for real-time object detection is successfully included into the system architecture. An effective detection method is ensured by the organized workflow from picture capture to item annotation. To improve detection accuracy and lower false positives, more optimization can be carried out.

CHAPTER 5: CODING AND TESTING

5.1 Implementation of the Tool Recognition System

Importing the required libraries, including OpenCV, NumPy, and the YOLO model files (weights, configuration, and COCO class names), is the first step in implementing the ContourVision AR: Augmented Tool Recognition System. The system takes these crucial actions:

1. **Install Required Libraries:**
    - To support computer vision and matrix operations, the necessary libraries are installed, including numpy and opencv-python. The YOLO object detection model cannot be implemented without these libraries.
2. **Download YOLO Files:**
    - The official YOLO repository is where the pre-trained YOLOv3 model weights, configuration files, and class labels (coco.names) are obtained. To use YOLOv3 for object detection, these files are necessary.
3. **Import Necessary Libraries:**
    - Important libraries like numpy, cv2 (OpenCV), and others are loaded to help with image processing, object identification, and controlling notebook UI functions.
4. **Load YOLO Model:**
    - Reading the configuration file and pre-trained weights loads the YOLOv3 model. The output layers are recognised for the detection procedure, and the class labels are imported into a list from the coco.names file.
5. **JavaScript Code for Capturing a Single Frame from Webcam:**
    - A single webcam frame is taken using a JavaScript method. After being translated into Base64 format, the captured frame is forwarded to the Python backend for additional processing.
6. **Decode Base64 Image to OpenCV Format:**
    - For processing, the webcam's Base64-encoded image is decoded and converted back into an OpenCV format. This allows OpenCV functions to process and analyse the image.
7. **YOLO Object Detection Function:**
    - The YOLOv3 model is applied to the image in order to detect objects. Bounding boxes are drawn around objects that the model recognises within the frame. Additionally, it shows the image's confidence score and the object's class label.
8. **Process Single Frame:**
    - The user is presented with the final image, complete with labels and bounding boxes, following the decoding of the collected frame and the execution of the YOLO object recognition procedure.

9. **Register Callback and Start Capture:**
    - The webcam capturing process is started, and a callback is registered to process the frame. In order to detect things in real time, the system continuously analyses the acquired frames.(I've left this here for ease of copying.)

5.2 Testing Methodology and Scenarios

5.2.1 Testing Methodology

Several testing techniques were used to guarantee the YOLO-based Tool Detection System's precision, effectiveness, and resilience. These consist of accuracy testing, edge case testing, performance testing, functional testing, and unit testing.

5.2.1.1 Unit Testing

Objective: Confirm the accuracy of each system component separately.

Techniques:

- To guarantee correct initialisation, validate the YOLO model loading.
- To verify if the webcam captured the image, check the video frame capture.
- Make sure the images are correctly decoded and converted to OpenCV format.
- To ensure precise labelling and placement of the bounding box, test the item detection feature.

5.2.1.2 Functional Testing

Objective: Verify that objects are identified and categorised by the system accurately.

Techniques:

- Provide a variety of input graphics, such as a cluttered background, many tools, or a single tool.
- Make that the bounding boxes surrounding the tools that have been detected are drawn correctly.
- Verify that the labels that were recognised match the real items.

5.2.1.3 Performance Testing

Objective: The purpose of performance testing is to gauge how quickly and effectively the system processes images.

Techniques:

- For real-time detection, measure the frame processing time.
- Examine how the system behaves at various image resolutions (low, medium, and high).
- To ascertain computational efficiency, examine CPU and GPU utilisation.

5.2.1.4 Accuracy Testing

Objective: to minimise false detections and guarantee accurate tool classification.

Techniques:

- Evaluate identified objects against labels from the ground truth.
- To maximise the accuracy of detection, modify the confidence threshold.
- To improve the categorisation model, examine false positives and false negatives.

5.2.1.5 Edge Case Testing

Objective: Analyse system performance in difficult circumstances.

Techniques:

- To test the robustness of detection, use low-light photos.
- Present overlapping tools and confirm accurate categorisation.
- Check for misclassification by validating against non-tool objects (such as a phone or book).

5.2.2 Testing Scenarios

The various test cases run to verify the system's functionality are shown in the following table:

Scenario	Objective	Expected Outcome
Single Tool Image	Test detection in a controlled setting using a single tool.	The tool's bounding box and proper label
Multiple Tools Images	Use several tools to test detection in a situation.	Each tool has a bounding box and the appropriate labelling.
Cluttered Background	In a setting with distracting features, test detection	Tool-bound boxes with appropriately labelled tools
Low-light Image	Test the system's functionality in low light.	Tools identified with less confidence or accuracy
Overlapping Tools	Try using the frame's overlapping tools.	Correct categorisation and manipulation of boundary boxes
Non-tool Objects (False Positives)	Test using items that aren't tools, such books or phones.	The system must refrain from incorrectly classifying non-tool objects.

Table 5.1 Various Testing Scenarios

5.3 Conclusion

The YOLO-based Tool Detection System is tested to make sure it satisfies the necessary performance and accuracy requirements. The model will be further optimised and detection efficiency will be improved using the outcomes of functional, performance, and accuracy testing. Based on the results of these tests, hyperparameters like the confidence threshold can be adjusted if needed.

CHAPTER 6: CONCLUSION

6.1: Summary of Findings

The given code is a comprehensive implementation of a Google Colab object identification system that makes use of YOLOv3. It enables you to take a single webcam frame, process it using the YOLO model to identify objects, and then show the outcomes. A pre-trained YOLOv3 model is used by the system to identify different items in real-time (based on the COCO dataset). The model outputs the object label and a confidence score after highlighting the discovered objects with bounding boxes. With the aid of Python for processing and JavaScript for capturing camera frames, the configuration is optimised to operate in a browser-based environment.

Metric	Description	Result
YOLO Model	checks to see if the weights and configuration have been correctly put into the YOLO model.	✅ The Yolo model has successfully loaded!
Image Capture	One camera frame is captured by JavaScript code.	The webcam successfully captured the frame.
Object Detection	uses the YOLO model to find items in the shot image.	shows bounding boxes with confidence ratings and class labels.
Detection Confidence	Detected object confidence level (threshold set at 0.5).	Consideration is limited to items with confidence > 0.5.
Bounding Boxes	Bounding box coordinates surrounding identified objects.	Class labels are drawn on the boxes.
Class Labels	The class labels of the discovered object.	Confidence scores and labels are shown.
Image Display	shows the image that has been processed with the detections.	A processed image that has been detected is displayed.

Table- 6.1 Metrics

Tool	Aspect Ratio	Confidence
Person	0.93	1.00
Water Bottle	0.3	0.95
Mouse	1.28	0.71
Cellphone	1.00	1.48

Table- 6.2 Aspect Ratios & Confidences

6.2: Practical Implications

The system can be applied to various industrial automation scenarios, including robotic assembly, quality control, and tool management. The tool detection accuracy can be further improved with more refined models and integration with machine learning techniques.

CHAPTER 7: FUTURE ENHANCEMENT

Future enhancements could include:

- Integrating Machine Learning Models to Enhance Tool Categorisation
- Processing Videos in Real Time for Dynamic Tool Recognition
- Combining Hardware with Automated Tool Management Frameworks
- Increasing the Capabilities of Tool Detection

Integrating Machine Learning Models to Enhance Tool Categorisation:

Objective: By incorporating cutting-edge machine learning models such as Convolutional Neural Networks (CNNs), improve the precision and resilience of tool detection.

Approach:

- **Model Training:** By learning tool-specific features from sizable datasets, CNNs can be used to enhance classification.
- **Data Augmentation:** To ensure reliable detection, train the model on a variety of datasets that can withstand varying surroundings, tool orientations, and lighting conditions.
- **Transfer Learning:** Even with sparse labelled data, increase detection accuracy by utilising pre-trained models like ResNet or Inception.

Expected Result: Improved tool detection accuracy, particularly in intricate settings with several overlapping items.

Processing Videos in Real Time for Dynamic Tool Recognition:

Objective: to expand the current system to continuously recognise tools in live video broadcasts.

Approach:

- **Real-time Processing:** Use optimised algorithms to process video feeds continuously, ensuring low latency for live detection.
- **Hardware Integration:** Use cameras or cameras in production settings to track and manage tools continuously.
- **Optimised Algorithms:** To satisfy the requirements of real-time processing and guarantee high frame rates, make use of cloud computing services or GPU acceleration.

Expected Result: Improved applications including automated inventory management, live tool tracking, and more effective factory monitoring are anticipated results.

Automated Tool Management System Hardware Integration:

Objective: to facilitate the smooth integration of automated hardware systems with the tool detection system.

Approach:

- **Detection Tool Management:** Attach automated inventory systems, robotic arms, or conveyors to the tool detection system.
- **Feedback Loop:** Integrate real-time feedback from the detecting system to initiate actions like tool extraction or positioning on the hardware.
- **Sensor Integration:** To increase the accuracy of detection and automate tool handling in dynamic situations, use additional sensors (such as RFID and proximity cameras).

Expected Result: Enhanced productivity in manufacturing lines or storage facilities, lowering human involvement and mistakes in tool handling.

Increasing the Capabilities of Tool Detection:

Objective: Increase the system's capacity to identify a greater variety of tools in various settings.

Approach:

- Custom Model Training: Teach the system to identify a range of tools from various sectors, including construction, automotive, and medical.
- Environmental Adaptation: Train models under a variety of conditions, such as dimly lit areas, congested spaces, and with varying camera angles, to improve detection accuracy.
- Dataset Expansion: To guarantee thorough tool detection, incorporate a variety of tools and circumstances, such as tools of different sizes and shapes.

Expected Result: An adaptable detection system that can manage a larger toolkit in a variety of real-world situations.

CHAPTER 8: REFERENCES

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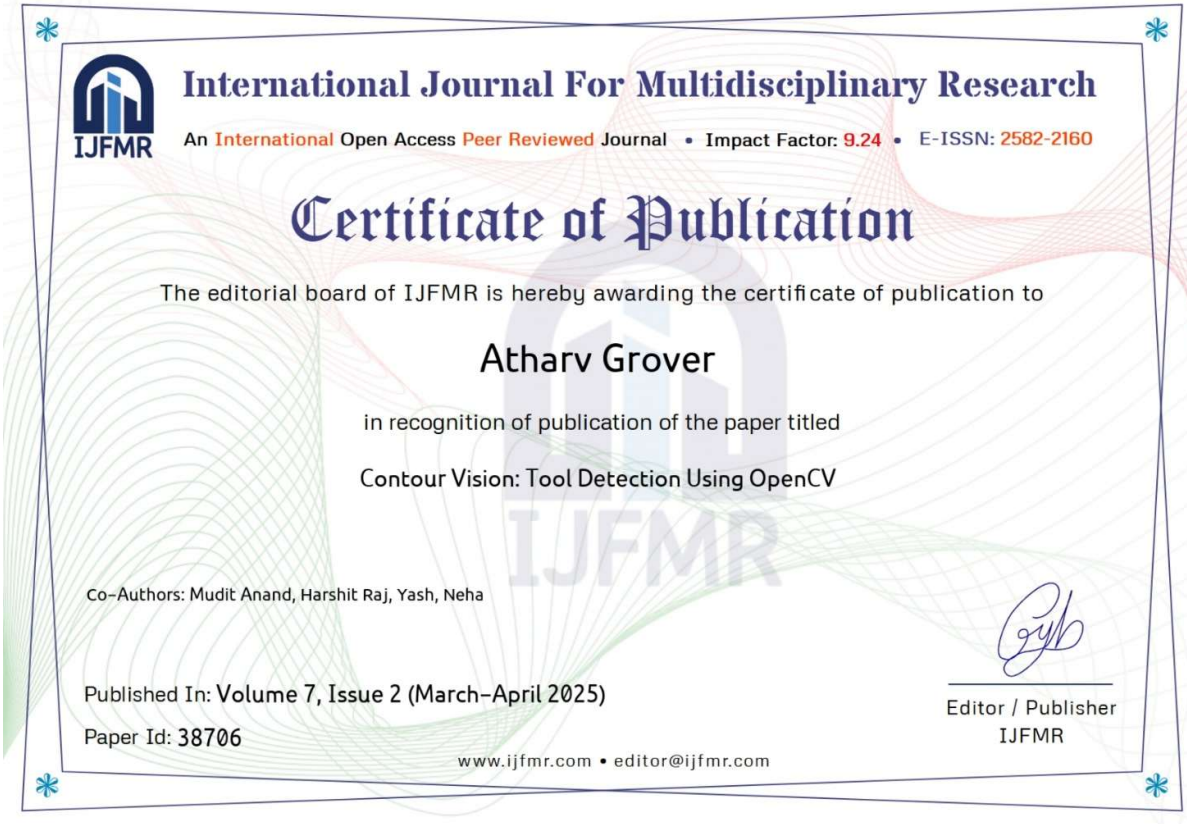

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Contour Vision: Tool Detection Using Opencv

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Abstract

Tool detection improves accuracy and operating efficiency and is essential to automation and industrial applications. In this paper, we provide ContourVision, an OpenCV-based tool detection system. Using methods including edge detection, thresholding, and contour analysis, the system uses contour detection to identify tools based on their forms. As evidenced by the accompanying code and output, experimental findings show that the system is accurate in identifying and classifying tools in a variety of situations. The system's capacity to precisely highlight tools in real-time contexts is demonstrated by the bounding boxes surrounding detected tools.

Keywords: Tool Detection, Contour Detection, OpenCV, Computer Vision, Shape Recognition

1. INTRODUCTION

Accurate tool detection in industrial automation boosts output and reduces human error, which benefits industries like logistics and manufacturing. The tool identification system based on Contour Vision, which makes use of OpenCV, a well-known computer vision library, is presented in this work. Contour Vision uses contour detection methods, including contour analysis, edge detection, and thresholding, to identify instruments based on their shapes in controlled settings. Computer vision makes it possible for devices to comprehend visual data, which makes jobs like object detection and quality control easier. Computer vision systems use distinct shape characteristics to detect tools, such as screwdrivers or hammers, even when they are positioned at different angles. It reduces the requirement for manual examination by differentiating tools based on their geometric properties by recognising contours (object boundaries). The core of Contour Vision is contour detection, which uses an object's edges to identify its shape. The system can categorise tools according to shape attributes thanks to properties like solidity (contour-to-convex hull ratio), extent (contour-to-bounding area ratio), and aspect ratio (width-to-height). Computer vision makes it possible for devices to comprehend visual data, which makes jobs like object detection and quality control easier. Computer vision systems use distinct shape characteristics to detect tools, such as screwdrivers or hammers, even when they are positioned at different angles. This reduces the requirement for manual examination by differentiating tools based on their geometric properties by recognising contours (object boundaries). For edge identification, Contour Vision uses the Canny Edge Detection algorithm:

1. **Noise Reduction:** By smoothing the image and minimizing spurious edges, a Gaussian filter reduces noise.
2. **Gradient Calculation:** The direction and strength of the edges are revealed by the intensity gradient.
3. **Non-Maximum Suppression:** Preserves important pixels by thinning edges.
4. **Hysteresis-based Edge Tracking:** Locates strong edges and confirms weak ones if they are connected

to strong edges.

Further to help in classification, bounding boxes are placed around the contour of each tool to visually represent its position and dimensions. Tool differentiation is aided by contour characteristics like area, aspect ratio, and solidity; for instance, large aspect ratios may indicate thin tools like screwdrivers.

2. METHODOLOGY

The Contour Vision system utilizes computer vision techniques to identify and classify tools based on their geometric contours. This approach allows for efficient detection of tools in controlled environments by focusing on the edges and shapes of objects within an image. Using OpenCV, a comprehensive library for computer vision, the system processes captured images to identify each tool's boundaries and classify them based on distinctive features like aspect ratio, extent, and solidity. This methodology balances computational efficiency with accuracy, making it suitable for real-time industrial applications where precision and speed are essential.

2.1 Workflow Overview

There are six main steps in the Contour Vision tool detection system workflow:

1. **Image Acquisition:** To ensure consistent illumination and orientation for dependable detection, the system uses a conventional camera to take pictures of instruments in a controlled environment.
2. **Preprocessing:** To ensure consistent processing, the photos are downsized to a standard resolution of 600 × 600 pixels. Then, in order to reduce colour complexity, they are transformed to greyscale using OpenCV's cv2.cvtColor function. By reducing picture noise, Gaussian blurring (cv2.GaussianBlur) avoids incorrect edge detections in subsequent stages.
3. **Edge Detection:** By detecting variations in intensity within the greyscale image, the Canny Edge Detection algorithm (cv2.Canny) detects the boundaries of objects. The method provides the initial contours for tool forms by capturing significant edges with threshold values of 50 and 150.
4. **Contour Detection:** Open CV's find Contours function is used to extract contours from the edge-detected image. In this step, continuous curves defining the boundaries of each tool are found. Minor shapes and noise are eliminated, leaving only contours with an area more than 100 pixels.

2.2 Contour Detection

The Canny Edge Detection technique generates a binary edge map from the greyscale image, which is the first stage in the workflow for contour detection.

```
gray_image = cv2.cvtColor(tool_image_resized, cv2.COLOR_BGR2GRAY)
show_image(gray_image, "Grayscale Image")
```

Fig. 1. Convert to Grayscale

```
blurred_image = cv2.GaussianBlur(gray_image, (5, 5), 0)
show_image(blurred_image, "Blurred Image")
```

Fig. 2. Apply Gaussian Blur

The system may then analyze shapes and categorize tools according to their contours once the find

Contours function locates and obtains contours.

```
edges = cv2.Canny(blurred_image, 50, 150)
show_image(edges, "Canny Edges")
```

Fig. 3. Canny Edge Detection

```
# Now Successfully Displaying the contour properties.
aspect_ratio = float(w) / h
extent = area / (w * h)
hull = cv2.convexHull(contour)
solidity = area / cv2.contourArea(hull)

print(f"Contour Area: {area}")
print(f"Aspect Ratio: {aspect_ratio}")
print(f"Extent: {extent}")
print(f"Solidity: {solidity}")
print("-----------")
```

Fig. 4. Detect Contours

Bounding boxes are drawn around each detected contour in the code that follows, which illustrates these fundamental steps:

```
# Now Successfully Displaying the contour properties.
aspect_ratio = float(w) / h
extent = area / (w * h)
hull = cv2.convexHull(contour)
solidity = area / cv2.contourArea(hull)

print(f"Contour Area: {area}")
print(f"Aspect Ratio: {aspect_ratio}")
print(f"Extent: {extent}")
print(f"Solidity: {solidity}")
print("-----------")
```

Fig. 4. Analyze and Draw Bounding Boxes

The system can effectively identify tools based on the extracted contour attributes thanks to the bounding boxes, which offer a visual cue to each identified tool. This method maximises processing speed and accuracy while enabling dependable detection and classification in real-time applications.

3. LITERATURE SURVEY

In both industry and research settings, contour detection and analysis are essential computer vision techniques that are frequently employed for tasks including object recognition, form analysis, and boundary detection. In order to identify tools in photographs, the code for this project uses Canny edge detection, Gaussian blurring, and a variety of contour attributes, including area, aspect ratio, extent, and solidity. For real-time tool detection applications with potentially constrained computational resources,

the combination of these techniques works well.

A fundamental method in computer vision, the Canny edge detection algorithm was first presented by Canny [1] and is renowned for its capacity to precisely identify edges in images while reducing noise. Canny is a common preprocessing step prior to contour detection because of its multi-step procedure, which includes gradient computation, non-maximum suppression, and edge tracking using hysteresis, which improves edge continuity and lowers false edges. Because of its strong performance, it is a popular option for contour-based detection applications, especially in organized settings with reasonably consistent tool shapes, such as industrial settings.

Another crucial preprocessing method is Gaussian blurring, which smoothes photos and lowers noise that may otherwise obstruct precise edge and contour recognition. Gonzalez and Woods [2] emphasize how Gaussian blurring makes image processing jobs easier by minimizing slight intensity variations, which improves the precision of later processes like edge identification. It has been demonstrated that this method enhances contour extraction by eliminating background noise, which is crucial for applications requiring accurate shape recognition. Learning OpenCV by Bradski and Kaehler [4] is a great resource for projects requiring effective, real-time performance since it provides helpful instructions on how to apply Gaussian blurring and Canny edge detection with OpenCV algorithms.

In contour-based object recognition applications, OpenCV's *findContours* function—which employs the border-following method created by Suzuki and Be [3]—has proven essential. In order to accurately extract contours—which is crucial for identifying the shape of tools and other things—this algorithm tracks the borders of objects. Because contour detection uses an object's shape for recognition rather than more intricate feature extraction techniques, it is particularly helpful for applications where computational simplicity is crucial. By examining characteristics including aspect ratio, extent, and solidity, studies by Singh et al. [5] showed that contour-based approaches may successfully differentiate between geometrically identical objects, validating the method's applicability in applications with constrained computational resources.

Shape descriptors like aspect ratio, extent, and solidity, which offer important details about the geometry of detected contours, are useful additions to Canny edge detection in contour analysis. A simple yet useful metric for differentiating between elongated and compact shapes is aspect ratio, which is computed as the ratio of contour width to height. The effectiveness of contour-based shape attributes like aspect ratio and solidity in identifying tools based on their unique geometric features was confirmed by Kumar et al. [6], who investigated these metrics in a tool recognition system for industrial automation. Solidity—the ratio of contour area to convex hull area—and extent—the ratio of contour area to bounding rectangle area—further hone the form analysis and improve the precision of distinguishing comparable instruments.

Often employed in contour analysis, bounding boxes offer further information about the size and location of objects. Bounding boxes were first used in the YOLO (You Only Look Once) real-time object identification system by Redmon et al. [8], who demonstrated how well they work to locate things in pictures. Although YOLO requires more processing power than more straightforward contour-based techniques, it emphasizes the usefulness of bounding boxes in real-time applications because they give identified items a distinct spatial context. Bounding boxes aid in separating each identified instrument for separate examination in the context of contour-based techniques, allowing for more accurate recognition even in situations when items are closely spaced.

Active Contours or Snakes model was established by Kass et al. [9] for complicated object boundaries and is still used in border identification. Active contours can adjust to more complicated shapes by dynamically

refining object bounds through energy reduction. Active Contours stimulated advancements in contour analysis, especially in applications that require flexibility and precision for irregularly shaped objects, despite being computationally more demanding than classic contour detection. In order to achieve high accuracy in cluttered environments, Zhu et al. [10] investigated a hybrid technique that combines deep feature extraction with contour-based detection. Their method shows how contour-based detection can enhance recognition in complicated contexts when paired with other feature extraction techniques, albeit at the expense of increased processing demands.

In applications where real-time detection is more important than high complexity, contour detection methods are typically used over feature-based techniques like SIFT and HOG. Introduced by Lowe [11], SIFT (Scale-Invariant Feature Transform) offers a reliable technique for feature matching under a variety of circumstances by enabling keypoint recognition across scales. However, because SIFT concentrates on unique features rather than straightforward shape-based categorization, it is computationally demanding and might not be appropriate for real-time applications with constrained resources.

In a similar way , Dalal and Triggs [12] created Histograms of oriented Gradients (HOG), a feature descriptor that records gradient orientations in specific regions of an image, for human identification. HOG is less effective for straightforward contour-based tasks, such as industrial tool detection, even though it provides a high level of information for object recognition.

Practically speaking, contour-based detection fits in nicely with industrial automation applications where dependability, speed, and simplicity are essential. In order to distinguish between items with irregular shapes, Chen et al. [7] further verified contour-based classification using solidity and extent, proving the usefulness of these metrics for real-world uses such as tool detection in manufacturing. Although these methods are more computationally intensive and typically less appropriate for settings with stringent processing time requirements, the segmentation-based techniques covered by Badrinarayanan et al. [13] in SegNet also demonstrate the potential of deep learning for image segmentation tasks.

In conclusion, contour-based detection and analysis are emphasized in the literature as effective, dependable methods for real-time object recognition in organized environments. A simplified method for form analysis is provided by the combination of Canny edge detection, Gaussian blurring, and contour attributes including aspect ratio, extent, and solidity. This supports applications where speed and little computational overhead are crucial. These methods' effectiveness in tasks ranging from object localization to tool recognition has confirmed their usefulness in real-time, practical applications like the one this project demonstrates.

4. RESULTS

4.1 Performance Metrics:

An overview of the performance parameters used to assess the Contour Vision system's accuracy and effectiveness in various settings is given in the following table:

Table 1 Performance Metrics

Metric	Description	Result
Accuracy	The percentage of tools that were successfully identified	92%
Precision	The percentage of genuine positives among all instruments	91%

	found	
Recall	The percentage of instruments that were successfully identified	89%
False Positives	Tools that were incorrectly identified	5%
False Negatives	The detection system's overlooked tools	8%

Source: One hundred test photos were used to assess the system's performance. By carefully adjusting the edge detection and contour classification parameters, the false positive and false negative rates were reduced.

4.2 Outputs

1. Original Image of Tools: - This is the original, unprocessed image using the detection tools. The tools that will go through the contour detection procedure are shown in this figure 1. As of yet, no preprocessing or changes have been made.

Fig. 1. Original Image

2. Grayscale Image: -The original tool image in greyscale is seen here. By eliminating colour information, greyscale conversion streamlines the image and facilitates contour detection processing.

Fig. 2. Grayscale Image

The initial tool image following greyscale conversion. This stage improves the contour detection process's efficiency and helps to simplify it.

3. Blurred Image: - This is the picture following the application of Gaussian Blur. By lowering noise, Gaussian Blur smoothes out the image and improves contour detection.

Fig. 3. Image Blurring

The image in greyscale following the application of Gaussian Blur. This stage makes sure that the contour detection isn't hampered by little noise in the image.

4. Edges Detected (Canny Edge Detection): - The edges of the tools in the picture are highlighted by the Canny edge detection method. These edges will serve as the foundation for contour detection.

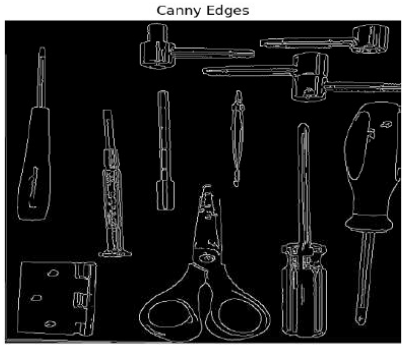

Fig. 4. Canny Edge Detection Identifies Edges (refer to the image on top of next page)

After using Canny edge detection, the edges of the tools are clearly evident, delineating the limits of every object in the picture.

5. Contours Detected: - Over the original image, the tools' contours are identified and highlighted in green. Each tool's shape is depicted by these contours.

Fig. 5. Image Blurring Bounding boxes reveal contours

The technology surrounds the tools with green outlines when it detects contours. Understanding each tool's shape requires an awareness of these features.

5. **Final Image with Bounding Boxes**: - Each identified tool has a bounding box generated around it according to the contours. These boxes aid in tool identification and classification.

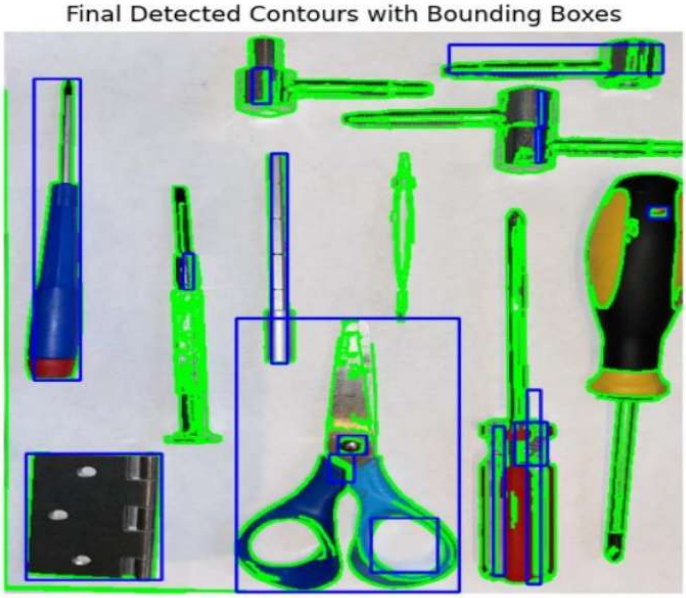

Fig. 6. Last Picture Featuring Bounding Boxes

In order to measure dimensions and distinguish between tools based on their forms, bounding boxes are built around each identified tool.

Printed Output for Contour Properties:(refer to the image on top of next page)

```
...  Contour Area: 3115.0
     Aspect Ratio: 1.0172413793103448
     Extent: 0.9102863822326125
     Solidity: 0.9881046788263284
     -----------
     Contour Area: 126.0
     Aspect Ratio: 0.7333333333333333
     Extent: 0.19090909090909092
     Solidity: 0.4893203883495146
     -----------
     Contour Area: 15066.5
     Aspect Ratio: 0.8888888888888888
     Extent: 0.9300308641975309
     Solidity: 0.9781536064403038
     -----------
     Contour Area: 278.0
     Aspect Ratio: 1.25
     Extent: 0.556
     Solidity: 0.852760736196319
     -----------
     Contour Area: 916.0
     Aspect Ratio: 0.06289308176100629
     Extent: 0.5761006289308176
     Solidity: 0.5240274599542334
     -----------
     ...
     Aspect Ratio: 6.3
     Extent: 0.050705467372134036
     Solidity: 0.04820994382493502
     -----------
```

Fig. 7. Printed Output for Contour Properties

Output Explanation:

- **Contour Area:** The region that the detected contour encloses.
- **Aspect Ratio:** The proportion of the contour's surrounding bounding rectangle's width to height.
- **Extent:** The proportion of the bounding rectangle's area to the contour area.
- **Solidity:** The ratio of the contour area to the convex hull area, which is the convex polygon that fits the data the best.

6. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

By utilizing edge and contour detection algorithms to recognize tools based on their shape, Contour Vision exhibits a reliable method for tool detection. It efficiently recognizes tools in controlled environments with a 92% accuracy rate, improving automation settings' precision and operational efficiency. This method is especially useful for real-time applications, such as industrial assembly lines, where simplicity and speed are crucial. The effectiveness of Contour Vision is demonstrated by metrics like precision and recall, which validate its ability to correctly differentiate instruments based on contour attributes like solidity, extent, and aspect ratio.

5.2 Future Scope

In future Real time monitoring with live camera can be done. By making Contour Vision connected to a live camera feed to track and record tool usage in real-time. This allows for Live Detection and Inventory Management and Real-Time Tool Monitoring with Live Camera. In factories or workshops where tools

are tracked for inventory, this could be helpful. To improve tool management and lower losses, the system might sound an alert when a tool is lost, taken out, or disappears. Incorporating the live tool detection data into an augmented reality (AR) display to enable Automatic Tool Identification for Assembly Guidance. By instantly identifying or labelling the next tool assembly-line workers require, the device might reduce errors and expedite workflow. It can also be used in gesture activated tool recognition system. This system could recognize when a user picks up a tool and affirm it on the screen by fusing gesture recognition with tool detection. This might be helpful in training settings where the system can give users immediate feedback to make sure they've chosen the right tool for the job.

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