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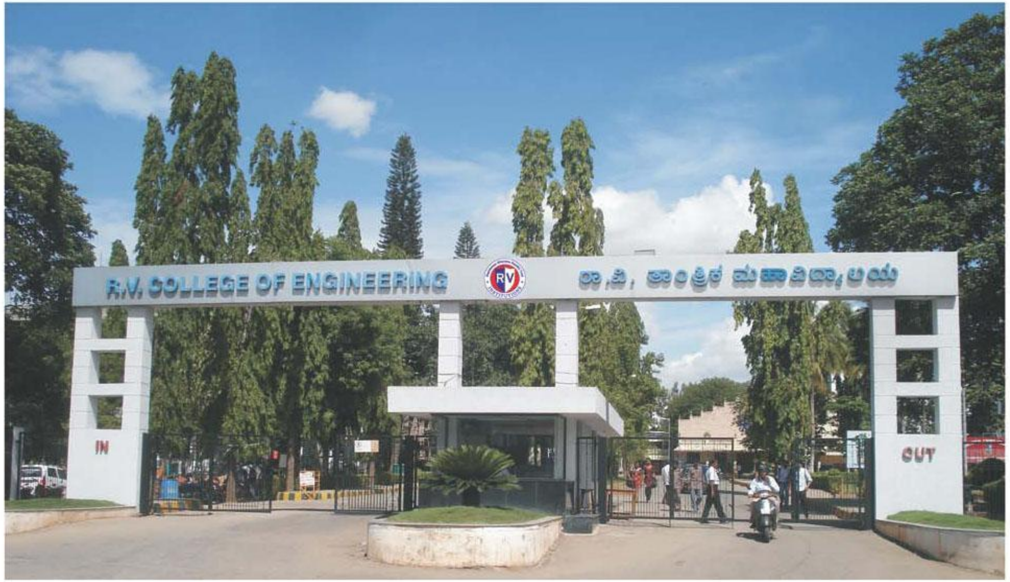


INTERDISCIPLINARY PROJECT (XX367P)

Topic : Real Time Cashew Kernel Classification Using Deep Learning

Team Details

Program	USN	Name
ECE	1RV23EC408	RAVIKANT
ECE	1RV23EC410	SAGAR T NAYAK
CSE	1RV23CS405	KIRAN H R
CSE	1RV23CS407	MANOJ KUMAR B V
BT	1RV23BT404	YOGEESH A S

Internal Guide

Dr. Veena Devi S .V

Associate Professor

Department of Electronics & Communication Engineering

INTRODUCTION

Cashew kernels are a valuable product in the global food market, and their quality affects both price and consumer choice. Traditionally, kernels are graded by hand based on size, shape, color, and surface condition. Skilled workers visually inspect and sort them into their respective grades.

However, manual grading is slow, tiring, and prone to mistakes, leading to inconsistencies in quality and profit loss. To solve this, the industry is moving toward automation using artificial intelligence and computer vision. Deep learning is especially useful because it can learn to recognize complex visual patterns from large sets of images.

This project focuses on developing a real-time system that automatically classifies cashew kernels using deep learning. It aims to replace manual inspection with a faster, more reliable, and scalable method, helping improve product quality, reduce labor needs, and boost overall efficiency in cashew processing.

INTRODUCTION

Fig 1. Commercial Grades of the Cashew

LITERATURE SURVEY

Paper Title, Author & Publication	Summary	Key Findings	Research Gap
Title: *A Low-Cost Deep-Learning-Based System for Grading Cashew Nuts.* **Authors:**Van-Nam Pham,Quang-Huy Do Ba , Duc-Anh Tran Le , Quang-Minh Nguyen , Dinh Do Van .(2024) **Journal:**journal *Computers*, Volume 13, Issue 3, Article 71, in March 2024.(published by MDPI,Q2)	The paper introduces an affordable, automated system that employs deep learning to grade cashew nuts. By integrating YOLOv8 with Transformer models, the system classifies cashew nuts into four quality grades and utilizes an actuation mechanism for physical sorting.	• YOLO v8, Transformer model offers 98.4% mAP and 2.96% error rate, outperforming baselines. • supports cost-effective industrial cashew sorting.	• Only focused on 4 types which include good, error1, error 2, error 3 • Lack of real-time cashew grading systems on conveyors using low-cost cameras. • Performance may vary based on the quality and specifications of the hardware used.

LITERATURE SURVEY

Paper Title, Author & Publication	Summary	Key Findings	Research Gap
Title: *Precise Cashew Classification using Machine Learning* **Authors:** Sowmya Nag Karnam, Veenadevi Siddanahundi Vaddagallaiah, Pradeep Kooganahalli Rangnaik, Akshaya Kumar, Charan Kumar, Bidadi Mahesh Vishwanath. **Journal:** Engineering, Technology & Applied Science Research, Vol. 14, No. 5, Oct. 2024(Q2)	The study evaluates deep learning models (YOLOv5, YOLOv9, CNN) for classifying cashews into five categories: whole, broken, split-up, split-down, and defect. YOLOv5 achieves 97.65% accuracy and 0.025 s inference time, making it ideal for real-time industrial applications.	• YOLOv5 outperforms YOLOv9 and CNN with the highest accuracy (97.65%) and fastest inference time (0.025 s/image). • Data augmentation enhances model robustness against variations in lighting and orientation.	• It also lacks discussion on handling environmental factors like lighting variations or nut-splitting phenomena, which are critical for industrial deployment. • Does not taken Hybrid model for case study • only focused on 5 categories.

LITERATURE SURVEY

Paper Title, Author & Publication	Summary	Key Findings	Research Gap
Title: *Implementation and Assessment of New Hybrid Model for Cashew Kernel Classification* **Authors:** Sowmya Nag K. and Dr.Veenadevi S. V **Journal:** International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING. (11/03/2024)(Q4)	The paper proposes nine hybrid models combining CNNs (VGG16, ResNet50, InceptionV3) with machine learning (SVM, RF, KNN) for cashew classification. ResNet-50 + SVM achieved 97.40% accuracy, outperforming manual and existing methods, suitable for industrial usage.	• ResNet-50 + SVM tops with 97.40% accuracy; VGG16 + RF at 95%, ResNet50 + RF at 90%. • Outperformed prior works, with accuracies up to 96.8% from existing studies.	• Lack real time implementation . • **Dataset Diversity**: does not include images from various sources and conditions (e.g., different lighting, backgrounds) would enhance model robustness.

LITERATURE SURVEY

Paper Title, Author & Publication	Summary	Key Findings	Research Gap
Title: *A Novel Approach to Cashew Nut Detection in Packaging and Quality Inspection Lines* **Authors:** Van-Hung Pham, Ngoc-Khoat Nguyen, Van-Minh Pham **Journal:** International Journal of Advanced Computer Science and Applications (IJACSA), Volume 13, Issue 12, 2022(Q3)	The paper proposes YOLOv7 for detecting cashew nuts (good, broken, not peeled) in packaging lines. YOLOv7-tiny achieves high accuracy with 6.2M parameters, suitable for real-time quality inspection.	• YOLOv7-tiny achieves high accuracy with 6.2M parameters, ideal for real-time cashew detection. • CASHEW dataset ensures robustness across brightness and angles, enhancing detection reliability.	• Lacks exploration of hybrid models combining YOLOv7 with techniques like CNN for improved accuracy. • Does not address real-time conveyor-based sorting with low-cost hardware integration. • does not include any market grading.

LITERATURE SURVEY

Paper Title, Author & Publication	Summary	Key Findings	Research Gap
Title: *CashNet-15: An Optimized Cashew Nut Grading Using Deep CNN and Data Augmentation* **Authors:** Sivaranjani, S. Senthilrani, B. Ashokumar, A. Senthil Murugan **journal:** Proc. Int. Conf. on Systems Computation Automation and Networking, 2019	Introduces CashNet-15, a 15-layer deep CNN architecture with data augmentation for binary classification of cashew grades (whole vs others). Uses 8 convolutional, 4 max-pooling, 1 fully connected, activation, and dropout layers. Achieves 97.7% accuracy, outperforming prior methods.	• Highest reported accuracy (97.7%) • Employs data augmentation to reduce overfitting • Custom CNN architecture optimized for the task • Hyperparameter optimization (SGD with Beta, LReLU)	• Only binary classification (whole vs others) • Limited grade granularity • Dataset size relatively small (1000 images) • No direct multi-class extension • Lack real time implimentation.

LITERATURE SURVEY

Paper Title, Author & Publication	Summary	Key Findings	Research Gap
Title: *An Improvised Algorithm For Computer Vision Based Cashew Grading System Using Deep CNN* **Authors:** Sivaranjani, S. Senthil Rani, B. Ashok Kumar, A. Senthil Murugan IEEE, 2019	Proposes an improvised deep CNN-based framework for automated grading of cashew nuts, addressing the limitations of manual and traditional machine learning approaches. The system extracts features (shape, size, color, texture) automatically and optimizes CNN parameters for better classification.	• Automates grading, reducing labor and subjectivity • Deep CNN extracts features without manual intervention • Incorporates optimization techniques (dropout, SGD, ReLU, transfer learning) • Potential for high accuracy and scalability	• Lacks experimental results or real-world deployment data • No direct comparison with state-of-the-art deep learning models • Future work needed to address multilabel and small dataset issues

MOTIVATION

The motivation behind this project arises from the need to address key challenges in kernel classification and sorting within the cashew processing industry.

- Through an in-depth literature survey, it was observed that existing solutions often lack real-time performance, scalability, and seamless integration between detection and actuation.
- To bridge this gap, we propose a comprehensive, real-time system that leverages YOLOv5s model for accurate Kernel grading, deployed on a Raspberry Pi for efficient edge inference.
- The classification results are communicated to an Arduino Uno, which controls stepper motors for precise physical segregation of kernels. This integrated approach combines deep learning, edge computing, and automated actuation offering a practical and scalable solution that moves beyond theoretical research toward real-world deployment.

PROBLEM STATEMENT & OBJECTIVES

Problem Statement:

Despite advancements in automated cashew kernel grading using machine vision and deep learning, existing systems face challenges in real-time processing, hardware constraints, image quality, defect detection, and dataset limitations. These issues hinder the development of efficient, accurate, and scalable grading solutions, impacting product quality, labor efficiency, and profitability in the cashew processing industry.

Objectives:

- Develop an image processing system to capture raw cashew kernel images and perform data preprocessing.(Data Collection)
- Design and implement algorithms for feature extraction, data analysis, and classification of kernel variations.
- Apply Deep Learning techniques to accurately detect, classify, and grade defects in cashew kernels.
- Integrate reliable hardware and software components for efficient, real-time testing and grading.

METHODOLOGY

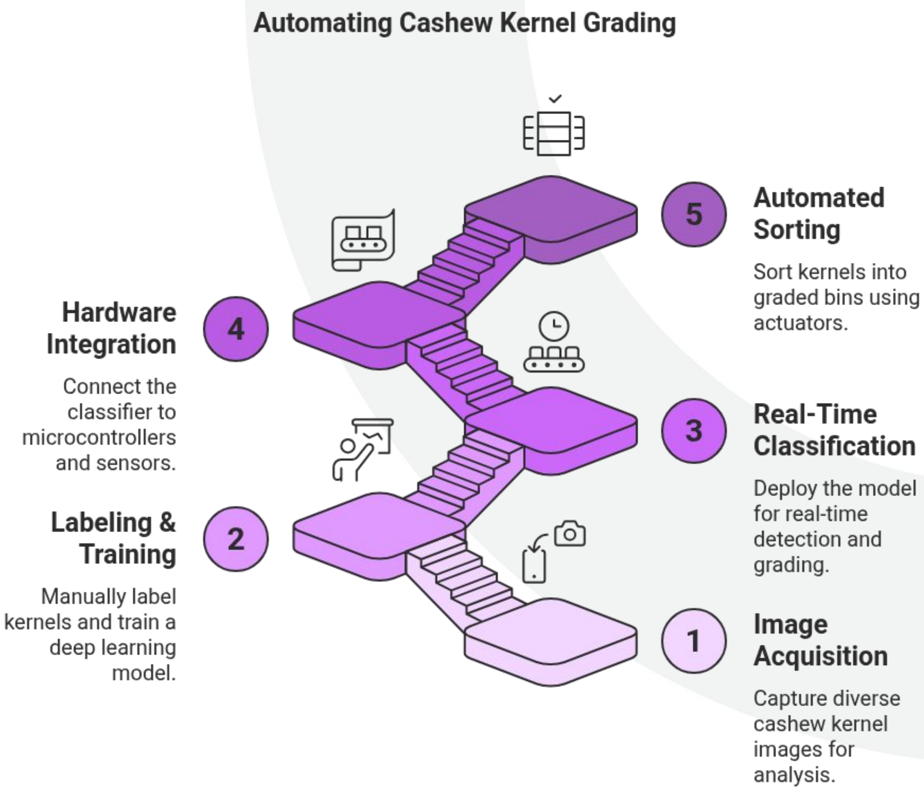


Fig 2. Proposed Methodology

METHODOLOGY

- **Image Acquisition**
  - Collect high quality images of cashew kernels under varying lighting, orientations, and backgrounds to ensure robustness.
  - Ensure class diversity by capturing images across all expected kernel grades and types to support effective model generalization.
- **Labeling and Training**
  - Manually annotate images with the corresponding kernel grades using labeling tools to create a reliable training dataset.
  - Train a deep learning model (YOLOv5s) on this dataset to enable accurate detection and classification of kernels by grade.
- **Real Time Classification**
  - Deploy the trained model on Raspberry pi to perform efficient, on-device interference.
  - Detect and classify kernels in real-time as they move through the processing line.

METHODOLOGY

- **Hardware Integration**
  - Connect Raspberry pi output to arduino uno, which acts as an interface between the classifier and actuators.
  - Use sensors and motor drivers to synchronize detection signals with mechanical movements for accurate sorting.

- **Automated Sorting**
  - Trigger stepper motors or actuators based on the classified grade to direct kernels into appropriate bins.
  - Achieve fully automated grading, reducing human error and increasing speed and consistency in the sorting process.

TOOLS & TECHNIQUES

1. **Python :** Core Model Development And Image Processing Task.
2. **OpenCV :** For image preprocessing, enhancement, and feature extraction(grades is size,Bounding box dimensions Aspect ratio (width vs height), sharp).
3. **Albumentations:** A fast and flexible Python library used to apply image augmentations like rotation, flipping, brightness changes, and noise to improve model robustness.
4. **Annotation Tool Used**
   a. Platform: Roboflow
   b. Annotation Type: Bounding Boxes
   c. Export Format: YOLO v5 (.txt) format
   d. Annotation Method: Manual drawing with class labels.
5. **Raspberry Pi 4 :** Compact single board computer used to run the model and to control hardware.
6. **Web Cam(Microsoft lifecam):** Used for Data Acquisition and also for capturing real time video for cashew grading.
7. **Arduino Uno:** Used to drive the motors for both conveyor belt and the actuators.
8. **Stepper Motors and Motor Drivers(L298N):** Used to precisely control the movement of sorting mechanisms based on classification output from the model.

TOOLS & TECHNIQUES

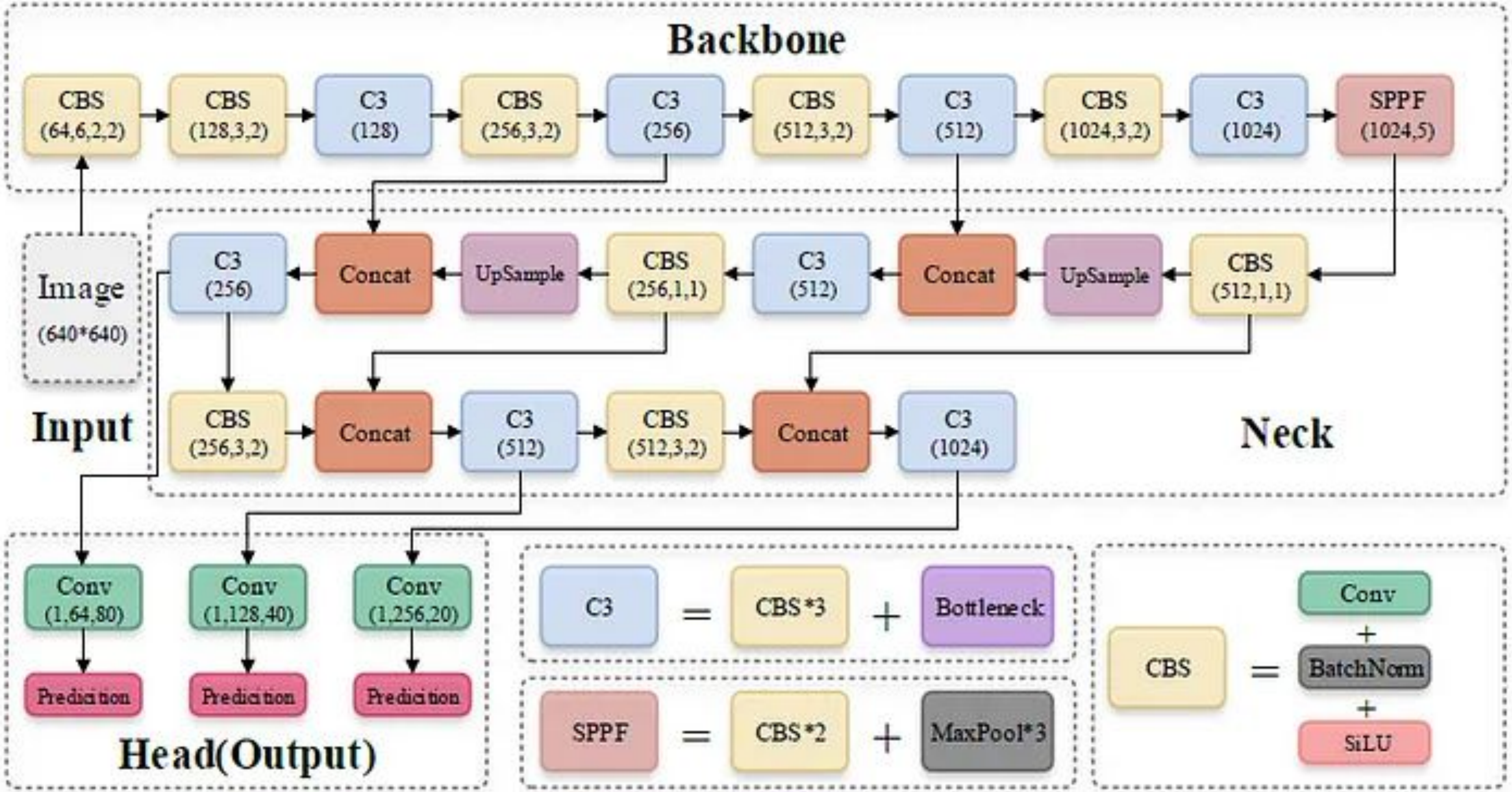


Fig 3. YOLO v5s Architecture

IMAGE/DATASET ACQUISITION

Dataset Development

Captured a substantial number of cashew kernel images using Microsoft Lifecam in varied lighting and orientations.

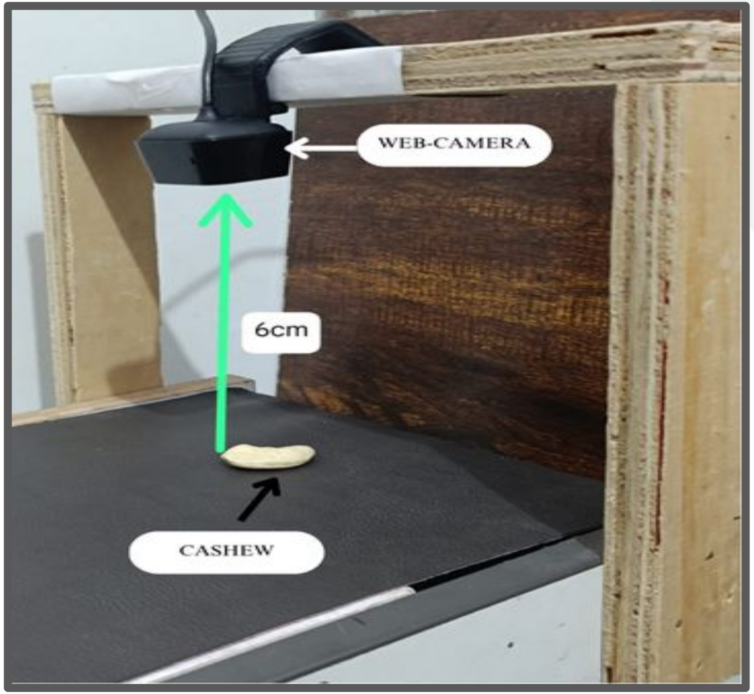


Fig 4. Image Capturing Setup

Images Captured		
GRADES	**NO. OF IMAGES**	**RESOLUTION**
W180	474	1280X800
W500	473	1280X800

DATA PREPROCESSING

2. Image Preprocessing:

Initial preprocessing steps such as:

- resizing (resized to 640x640)
- noise reduction
- image enhancement
- Data Augmentation

have been implemented to improve the quality of input data for Model Training .

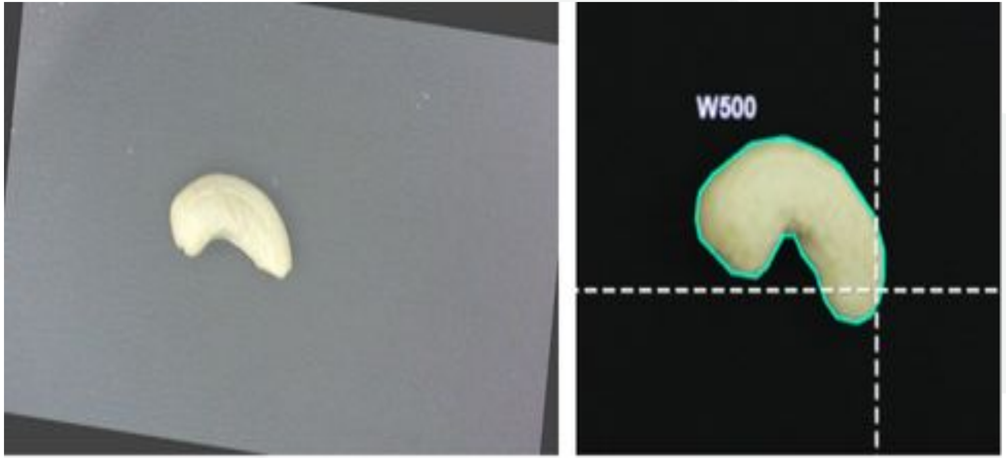


Fig 5. Normal Image vs Annotated Image

DATA PREPROCESSING

Noise Reduction

- To enhance image quality and minimize unwanted artifacts, noise reduction was performed using the Gaussian filtering algorithm.
- It applies a **Gaussian function** (a bell-shaped curve) to **blur** the image.
  - This is done by averaging each pixel's value with its neighbors, with closer pixels weighted more heavily.
  - It effectively removes **high-frequency noise** (random variation in brightness or color).

DATA PREPROCESSING

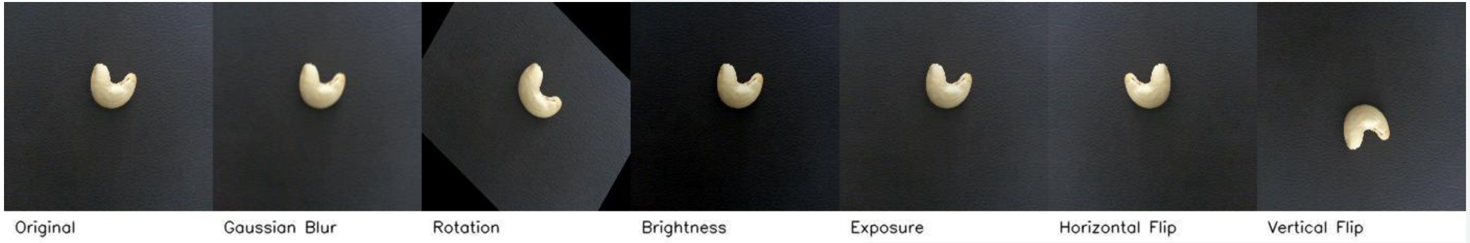
Image Enhancement:

- It used to **improve the visual quality** of an image or make certain features more distinguishable for further analysis.
- It helps in making key features (like cracks, textures, or object boundaries) **more visible** and **easier to detect**, especially in applications like cashew grading, medical imaging, or surveillance.

DATA PREPROCESSING

Augmentation Settings

- **Techniques Applied:**
  - **Blur:** Gaussian blur applied up to **5 pixels**
  - **Rotation:** Random angle between **-45° to +45°**
  - **Brightness:** Adjusted randomly between **-25% to +25%**
  - **Exposure:** Adjusted between **-10% to +10%**
  - **Flip:** Horizontal, Vertical



After Augmentation		
Grades	**No. of Images**	**Resolution**
W180	1891	640 x 640
W500	1890	640 x 640

LABELING AND TRAINING

Manually annotated all images with the corresponding kernel grades using labeling tool called Roboflow to create a reliable training dataset

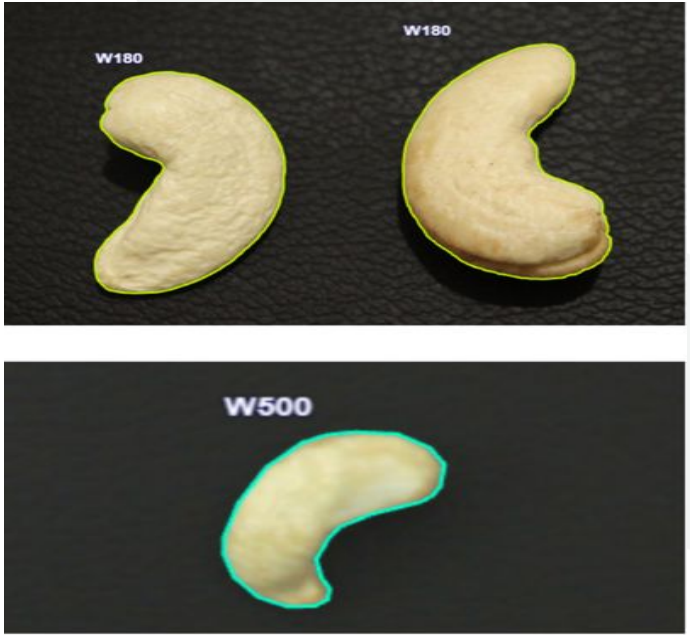


Fig 6. Sample Annotated images of the cashew grades

LABELING AND TRAINING

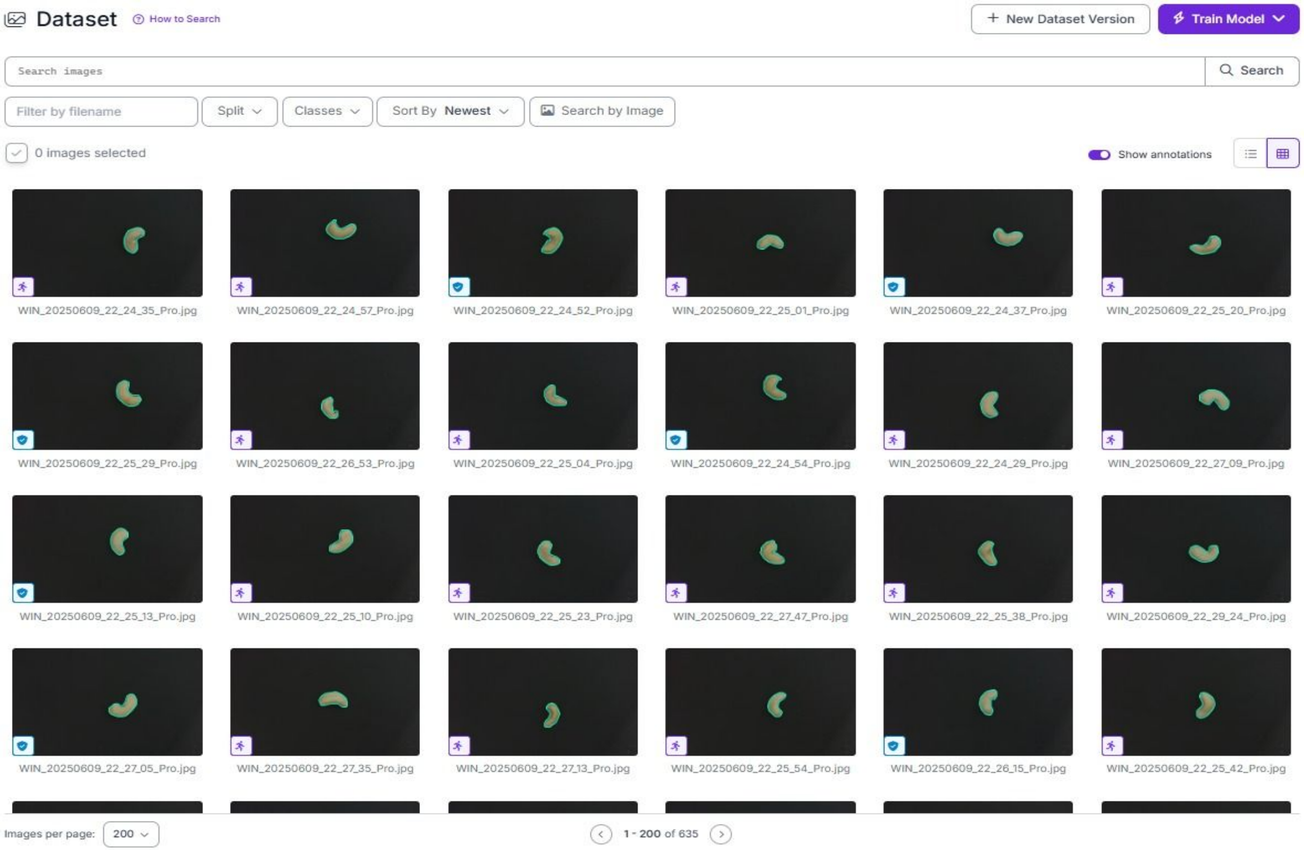


Fig 7. Annotated Dataset of the cashew grades

LABELING AND TRAINING

After dataset augmentation and Annotation , the model was trained under the following configuration to ensure optimal detection performance:

- **Image Size**: 640 × 640
- **Epochs**: 100
- **Batch Size**: 16
- **Learning Rate**: 0.01
- **Model Used**: YOLOv5s

Block Diagram

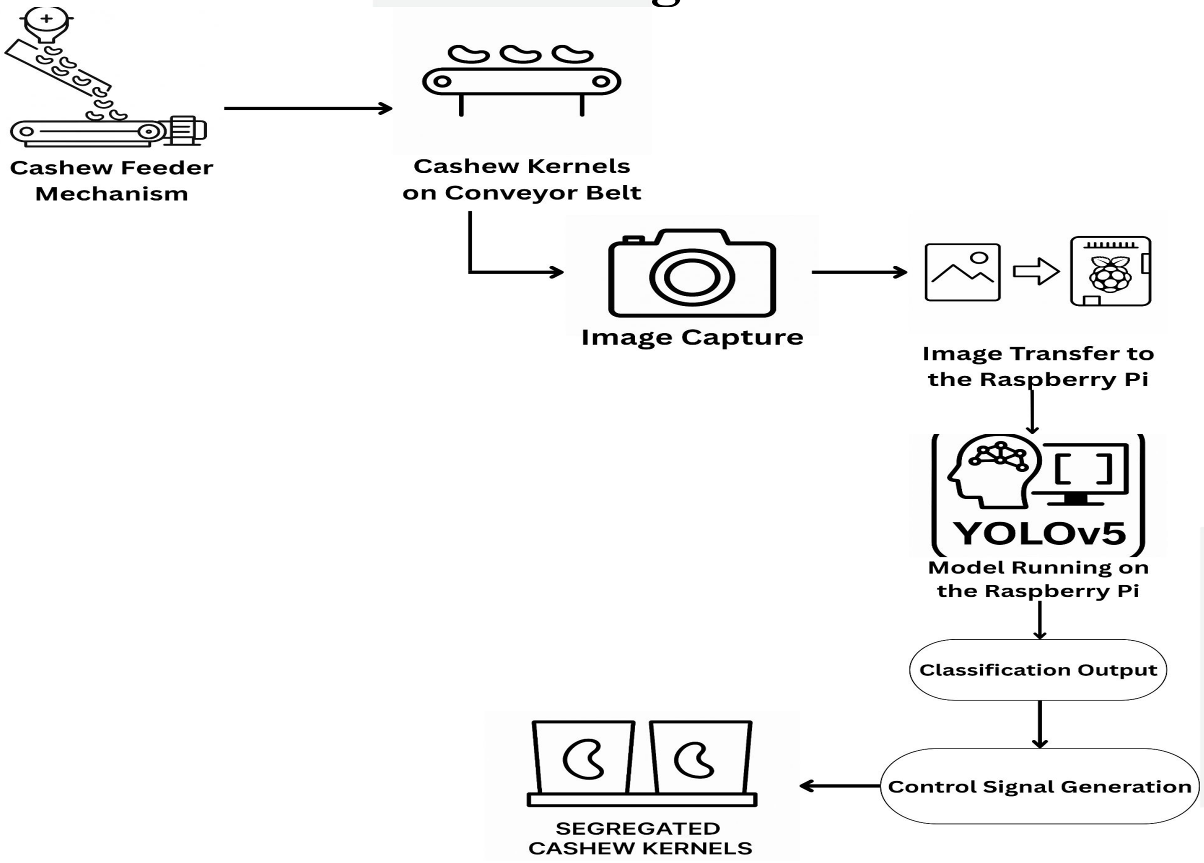


Fig 8. System Architecture and Workflow of the Automated Cashew Kernel Sorting Model

RESULTS

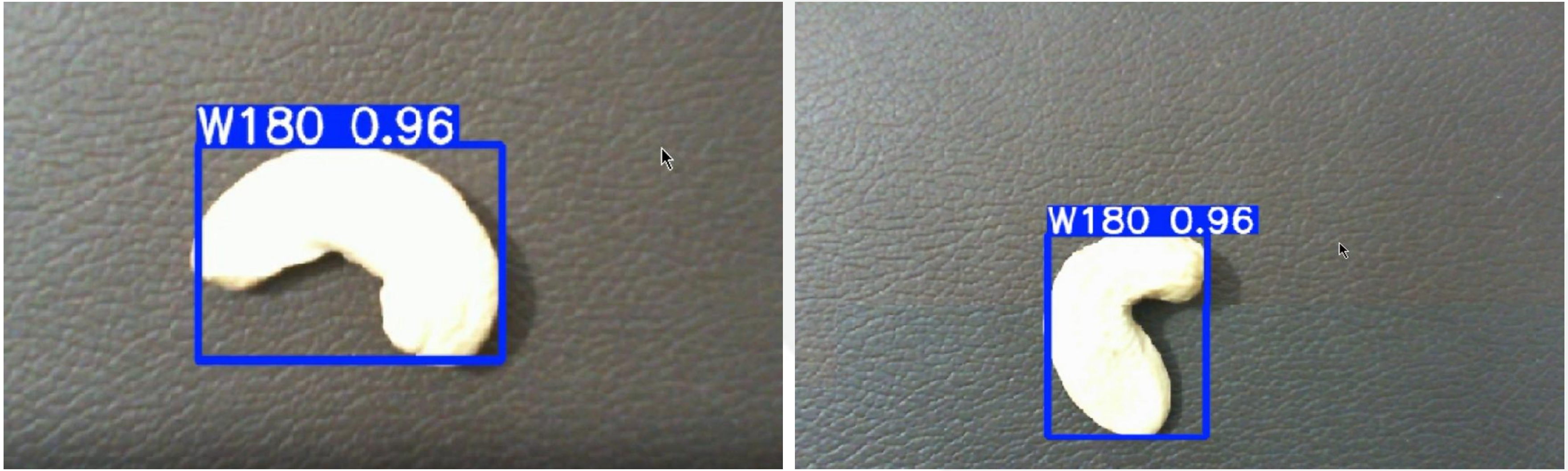


Fig 9. Model Classification Output of grade W180 grade

RESULTS

Fig 10. Model Classification Output of grade W500

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RESULTS

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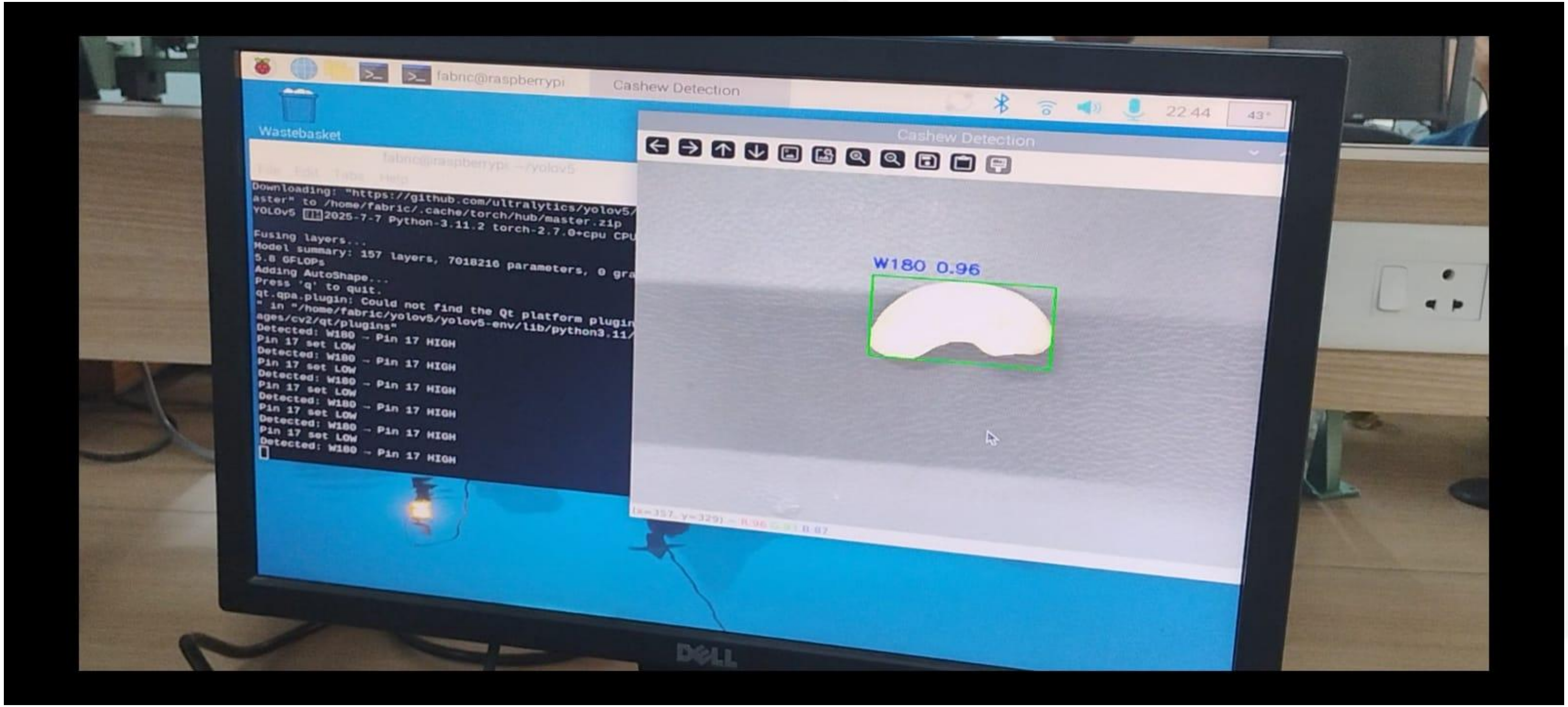

Fig 11. Live Cashew kernel classification on Raspberry pi

CONFUSION MATRIX

Confidence and Precision - Recall Analysis

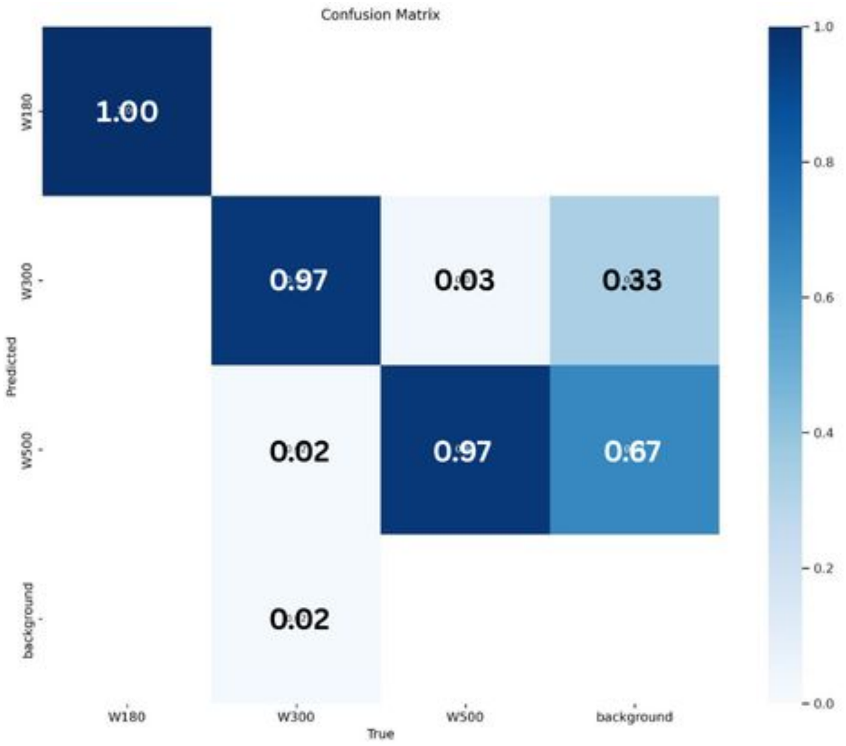

Fig 12. Confusion Matrix

- The **confusion matrix** illustrates clear and balanced classification across all three kernel grades: **W180, W300** and **W500**.
- Diagonal dominance in the matrix confirms high **true positive** predictions for all classes.
- **Minor confusion** observed:
  - A few **W300 kernels misclassified as W500**, likely due to close visual similarity in size/shape.
- **Overall distribution** remains well-separated, reflecting good inter-class distinction by the model.

This analysis confirms the model's robustness in multi-class detection tasks with minimal class confusion.

Results & Discussion

Confidence and Precision Recall Analysis

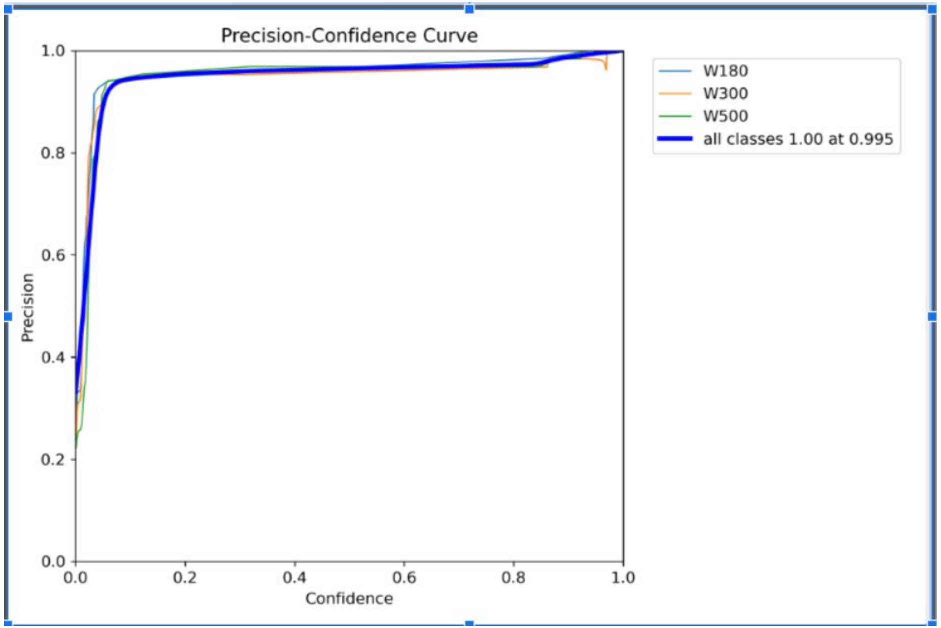

Fig 13. Precision - Confidence Curve

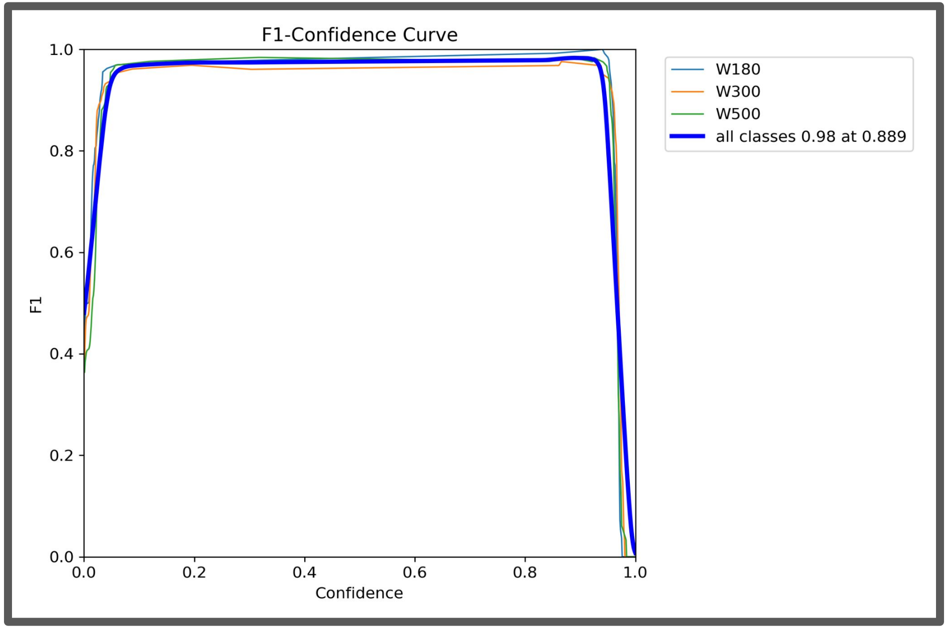

Fig 14. F1 - Confidence Curve

Results & Discussion

Confidence and Precision - Recall Analysis

❖ **F1–Confidence Curve**:

- Peaks at a **confidence threshold of 0.89**, achieving an **F1 Score close to 0.98**.
- Indicates optimal balance between **precision and recall** at that threshold.

❖ **Precision–Confidence Curve**:

- Shows **near-perfect precision (~1.00)** at a threshold of **0.995**.
- Indicates very low false positives at high confidence levels.

CONCLUSION

- Developed a real-time Deep Learning-based system for cashew kernel grading and sorting using YOLO V5s on Raspberry Pi 4.
- Achieved over **95% accuracy** with precise physical segregation via Arduino-controlled flaps.
- Offers a **low-cost**, **scalable**, and **efficient** solution for automating cashew processing, enhancing productivity and grading consistency.
- Sets the foundation for further industrial automation in agro-processing.

FUTURE SCOPE

- ➢ Expand grading to include more kernel types like W210, W240, and defective classes.
- ➢ Enable dynamic dataset generation for adaptive learning in real environments.
- ➢ Integrate edge AI accelerators (e.g., Jetson Nano) for faster, parallel processing.
- ➢ Add sensor feedback for error detection and real-time monitoring dashboards.
- ➢ Support bulk sorting using conveyors and object tracking (e.g., Deep SORT).
- ➢ Implement data logging for traceability and quality assurance in exports.

QR Code for Video Demo and Other Project Documents

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Thank You!