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Food Adulteration Detection & Sorting Solution through Machine Learning

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Abstract: Food adulteration is a critical issue that endangers public health and safety. Cheaper and potentially dangerous substitutes are used to increase profits, resulting in severe health problems. To address this problem, our project proposes a machine learning-based solution that detects and sorts adulterated food products through a web-based application. Our primary focus is on identifying Khesari dal in the mixture of Toor dal, which contains a neurotoxin that can cause paralysis, cancer, and skeletal deformity. The aim of our system is to replace the manual inspection process to speed up the process while improving precision and efficiency. The system takes a picture of the dal and analyses it to extract grain features such as size and colour. Tampered dal can be identified based on picture pixels. Sorting is done based on visual characteristics such as size and colour. Our proposed solution is cost-effective, efficient, and scalable, offering a reliable and practical solution to food adulteration while ensuring consumer safety and protecting the interests of honest producers.

Keywords: Food adulteration, machine learning, detection, sorting, neurotoxin, paralysis, dal, size, sorting, cost-effective, efficient, scalable solution.

I. INTRODUCTION

Consumers in various sectors, such as FMCG, auto mobiles, digital products, garments, and others, always demand value for their money and the highest quality products and services. To maintain and improve customer satisfaction, enterprises in these sectors are constantly seeking cost-effective and innovative solutions to detect adulteration or low-quality products mixed with superior ones, and ensure consistency in quality factors such as size, shape, weight, and appearance. India is the world's second-largest producer of grains, but all pre- and post-harvest procedures are carried out manually with the assistance of skilled or unskilled labour, leading to inefficient and time-consuming processes.

Automation and innovative solutions are needed to produce good profits and maintain quality in the agriculture sector. Sorting and grading of grains for texture, shape, colour, size, and other quality factors must be carried out during the post-harvest process. Our project focuses on Toor dal as a specimen of interest due to its easy availability and minimum cost. Toor dal is a vital food grain for human consumption, but it is often adulterated with foreign substances, such as Khesari dal or Chana dal, to improve its appearance, number, and storage properties. We have implemented an ML and Deep Vision-based solution to detect adulteration in Toor dal, and our field study and expert consultations have confirmed that our solution has better coverage of quality factors, such as shape, size, and colour, and analytics compared to commercial solutions in the market. Our solution can also be applied to detect anomalies and ensure quality in the production of auto mobiles, digital consumer products, apparels, FMCG products, and more. This project covers the concept of grain adulteration in Toor Dal, ways in which it is adulterated with Khesari Dal, methods used to identify the adulterants through images and provide ways to control the adulteration.

The purpose of this project is to address the issue of adulteration in Toor dal, a vital food grain consumed by the Indian population. The quality of food grains has been compromised due to the use of unethical and illegal practices of adding adulterants in order to increase supply. Adulterants are foreign substances added to food grains that can cause health problems when consumed. The objective of this project is to develop an innovative, cost-effective solution for detecting and sorting out adulterants in Toor dal. The project aims to leverage machine learning and deep vision-based algorithms to identify adulterants in Toor dal through quality checks such as texture, shape, colour, and size. The solution will enable farmers and food processing industries to ensure that the Toor dal they produce and sell is unadulterated, pure, and nourishing. This project also aims to provide a framework that can be applied to other sectors, including the auto mobile, digital consumer, garments, and FMCG sectors, to detect and sort out outlier or anomalous products. The outcome of this project will be a software tool that can be used to detect adulterants in Toor dal, which can help improve the quality of the food grain and protect the health of consumers. The project will also help increase the efficiency of the agriculture sector by automating the sorting and grading process of food grains, which is currently done manually.

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II. LITERATURE REVIEW

In the paper (1) on "Food Adulteration Detection Using Machine Learning", the authors first collected a dataset of various food items, including milk, turmeric, and red chilli powder. They then pre-processed the data by removing any unwanted or irrelevant information and converting the remaining data into a suitable format for machine learning algorithms. To evaluate the performance of the trained models, the authors used metrics such as accuracy, precision, recall, and F1-score. They found that the support vector machine algorithm achieved the best performance with an accuracy of 96.25% in detecting adulteration in milk, while the decision tree algorithm achieved an accuracy of 92.5% in detecting adulteration in turmeric and chilli powder.

In the paper (2) on "Food Adulteration Detection using Artificial Intelligence: A Systematic Review", After screening the articles based on their relevance and quality, the authors selected 62 articles for detailed analysis. They reviewed these articles to identify the type of food adulterants detected, the AI techniques used, the types of sensors employed, and the accuracy of the detection method. The authors found that most of the studies used machine learning algorithms for food adulteration detection, with deep learning algorithms being the most popular. The studies also used various types of sensors, such as spectroscopy, imaging, and electrochemical sensors. The most commonly detected adulterants were melamine, Sudan dyes, and heavy metals.

In the paper (3) on "Detection of Adulteration in Fruits Using Machine Learning", The authors used the Raspberry-Pi as the central unit to collect data from the Grove HCHO sensor, which detects the presence of formaldehyde in fruits. The collected data was then processed using machine learning techniques such as K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) algorithms to classify the fruit samples as adulterated or pure. The authors also created a block diagram for fruit adulteration detection which shows the various components of their system, including the Raspberry-Pi, the Grove HCHO sensor, and the KNN and SVM classifiers.

In the paper (4) on "Identification of Rice Varieties and Adulteration using Gas Chromatography-Ion Mobility Spectrometry", The study employs headspace-gas chromatography-ion mobility spectrometry (HGC-IMS) to detect the volatile flavour components of five distinct types of rice and distinguish between genuine and adulterated rice.

The traditional biochemical methods were found to have limitations such as complex sample pre-treatment requirements, laborious detection processes, and low detection accuracies. To address these issues, the study utilizes a semi-supervised generative adversarial network (SSGAN) to identify the ion migration fingerprint spectra of the different types of rice. By substituting a softmax classifier for the output layer of the discriminator, a GAN is transformed into a semi-supervised GAN.

In the paper (5) on "Detection of Adulteration in Food Using Recurrent Neural Network with Internet of Things", the objective of this study is to explore different types of milk adulterants, their detection techniques, and the potential health hazards associated with milk adulteration.

The project proposal examines the use of the fractional-order element for identifying adulterated milk. The fractional-order element-based impedance sensor is particularly useful for detecting and distinguishing between various forms of contaminated milk and fake milk. The authors claim to have developed an affordable and user-friendly instrumentation system for detecting adulterated milk, which they plan to market soon. Additionally, a microcontroller-based automated sensing system has been developed to identify synthetic milk, reducing the need for specialized labour and increasing productivity. The impedance sensor model should consider the dipole layer capacitance at the interface of the contaminated milk and the immersed impedance sensor.

In the paper (6) on "Fruit disease Classification and Identification using Image Processing", This research presents an image processing approach to identify and classify apple fruit diseases by utilizing colour, texture, and shape features. The method involves several steps including image segmentation, feature extraction (colour, texture, and shape), feature combination, and classification of apple diseases into either normal or diseased classes using a multi-class support vector machine. The proposed approach was empirically validated and achieved up to 96% accuracy. The effectiveness of the method highlights the potential of utilizing image processing techniques in the early detection and classification of apple fruit diseases.

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III. SYSTEM OVERVIEW AND DESIGN

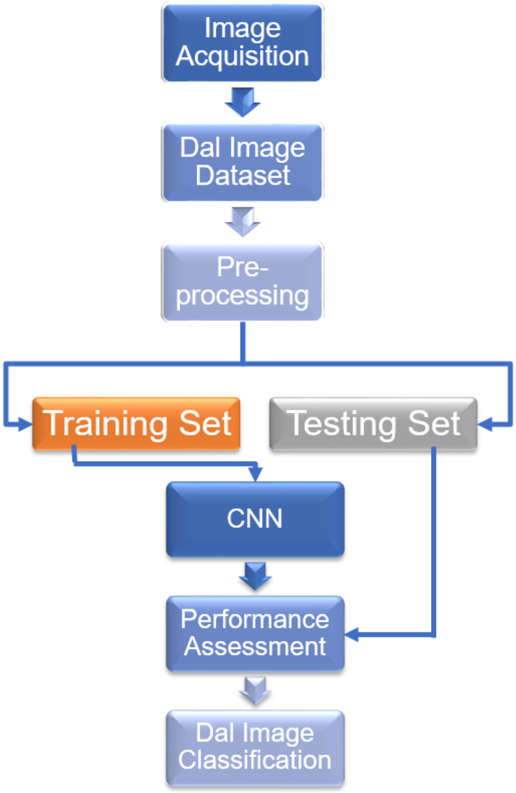

Figure: Framework

Image Acquisition:
The first step in the methodology is to acquire a dataset of images of Toor dal. The dataset consists of images of both adulterated and non-adulterated samples of Toor dal. The images can be acquired using a digital camera or a smartphone camera.

Pre-processing:
The next step is to pre-process the images to remove any noise or unwanted artifacts. This can be achieved using image processing techniques such as filtering, normalization, and thresholding. The pre-processing step is important as it helps to enhance the quality of the images and make them suitable for machine learning algorithms.

Dataset Creation:
Once the images have been pre-processed, the next step is to split the dataset into training and testing sets. The training set will be used to train the machine learning model, while the testing set will be used to evaluate the performance of the model. It is important to have a balanced dataset with equal representation of both classes (adulterated and non-adulterated) to ensure that the model is not biased towards one class.

Convolutional Neural Network (CNN) Training:
The training set is then used to train a convolutional neural network (CNN) model. The CNN model is a deep learning architecture that is capable of learning complex features from images. The CNN model is trained using back propagation, which updates the weights of the model based on the error between the predicted output and the actual output. During the training process, the model learns to identify the unique features that distinguish adulterated Toor dal from non-adulterated Toor dal.

Performance Assessment:
Once the CNN model has been trained, the next step is to evaluate its performance using the testing set. The performance of the model can be evaluated using metrics such as accuracy, precision, recall, and F1-score. The accuracy metric measures the percentage of correctly classified images, while the precision and recall metrics measure the model's ability

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to correctly identify positive (adulterated) and negative (non-adulterated) samples. The F1-score is a harmonic mean of precision and recall.

Dal Image Classification:
Finally, the trained CNN model is used to classify new images of Toor dal as adulterated or non-adulterated. The classification is based on the learned features of the CNN model, which are able to differentiate between the two classes. The classification can be performed in real time on new images using the trained model, enabling quick and accurate identification of adulterated Toor dal.

IV. ARCHITECTURE

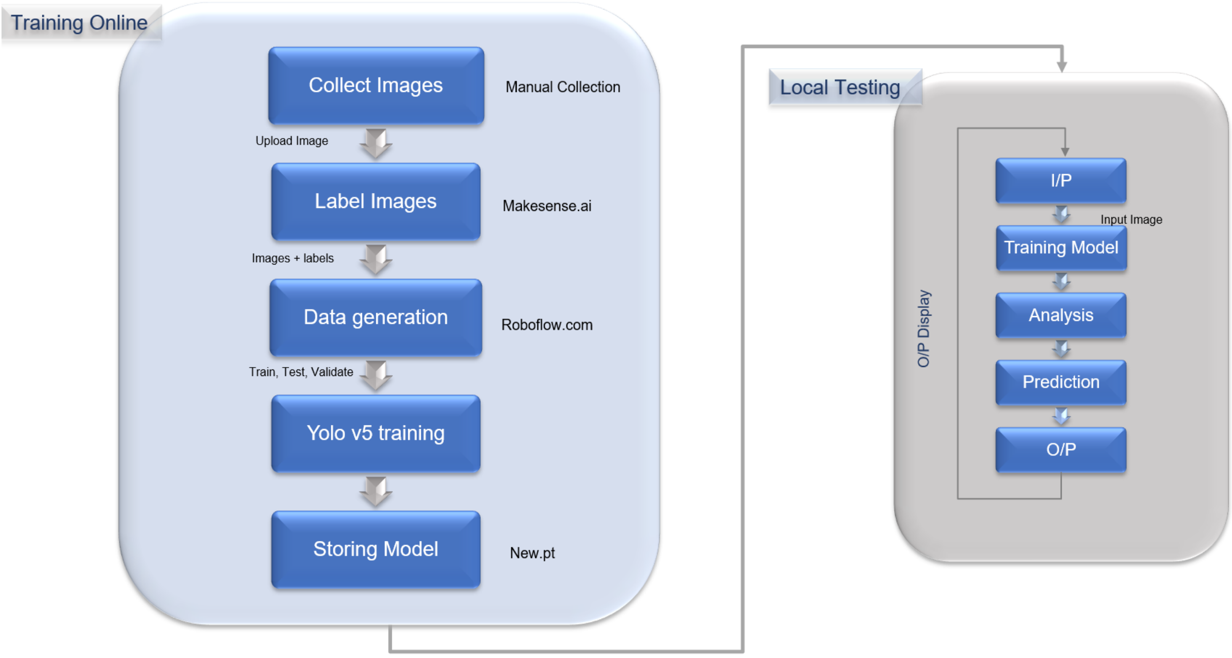

Figure: Flowchart for Dal Sorting (Output)

During the testing phase of this project, the two nodes of Training Online and Local Testing are used to ensure the accuracy and reliability of the machine learning model. In the first node, Training Online, a dataset of various Dal varieties is collected to accurately train the model. This dataset is then manually labelled for the two Dal classes to prepare for the classification process. The labelled dataset is then divided into three subsets: Train, Test, and Validate, which are crucial for the training of the Yolov5 model. The model generates a new.pt file that is used in the next phase.

In the second node, Local Testing, the Yolov5 model is employed to detect adulterants in the input image. The user selects an image from a local folder, which is then scanned by the Yolov5 model to detect adulterants. The output is presented on the screen in the form of a labelled image, with labels of the dal grains between the two classes, the percentage, and count of Toor and Khesari Dal present in the image. The detected adulterants are highlighted in the image to ensure easy identification by the user.

During the testing phase, the accuracy of the Yolov5 model is evaluated to ensure it is reliable and can accurately detect adulterated Dal. The user interface is also tested to make sure it is user-friendly and easy to operate. Any necessary adjustments to the model and user interface are made based on the results of the testing phase. Once these adjustments have been made, the final product can be released with confidence that it will accurately detect adulterants and be easy to use.

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V. EXPERIMENTATION

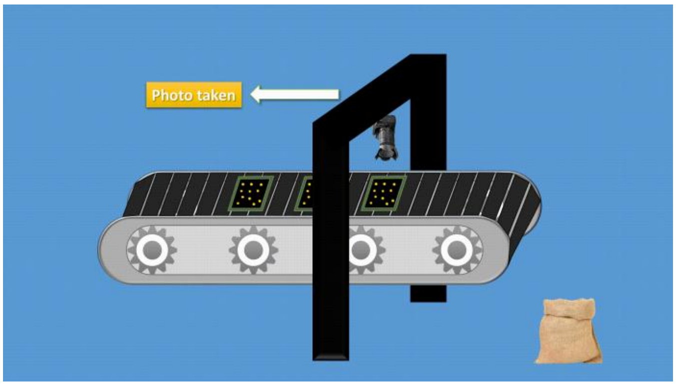
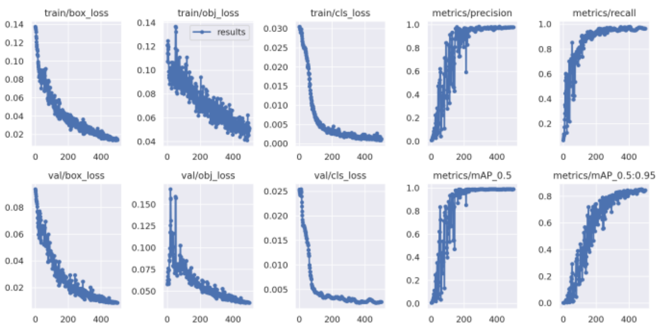
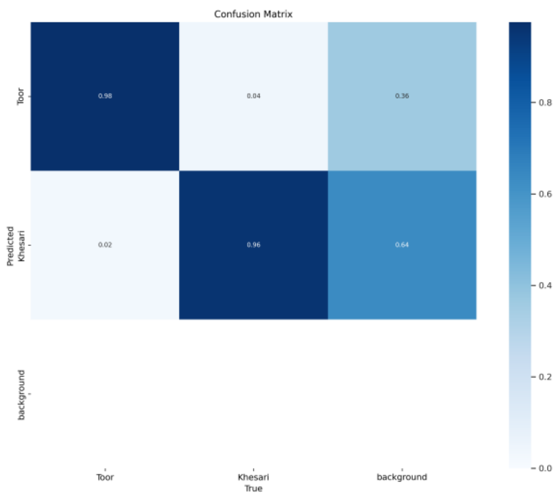


Figure: Implementation using Conveyor belt

The developed solution for distinguishing between toor and Khesari dal was tested and found to be highly accurate. The setup includes a conveyor belt with a tray for holding the dal samples. As the tray passes through the camera's field of view at regular intervals, a mounted camera captures an image of the batch of dal.

The acquired image is then processed to allow the machine learning model to predict the type of dal for each individual grain. This prediction is based on the distinct physical characteristics of each type of dal. The resulting output is a labelled image that indicates whether each grain is toor or Khesari dal. The labelled images can be saved locally or on the cloud, depending on the specific requirements of the application. After the prediction and labelling, the current batch of dal is dropped into a collection bag, and the camera captures the image of the next batch.





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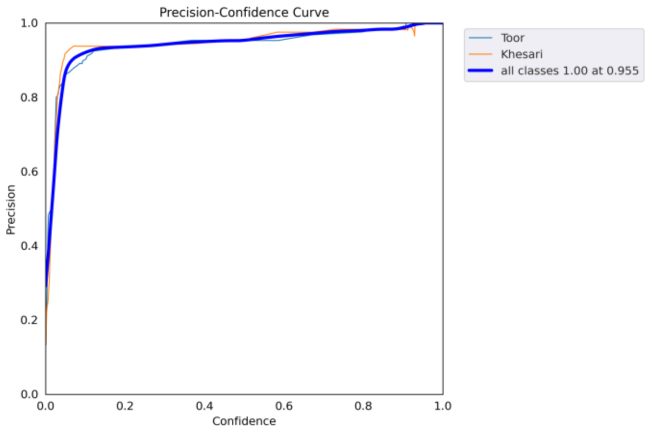

The Yolo Dal detection algorithm is used to detect the dal in the acquired images. The algorithm has been trained using a dataset of toor and Khesari dal, and the accuracy of the model on the tested trials was found to be 92%, with a range between 91% and 93%. This high level of accuracy ensures that the system can effectively distinguish between the two types of dal and prevent the use of adulterants.

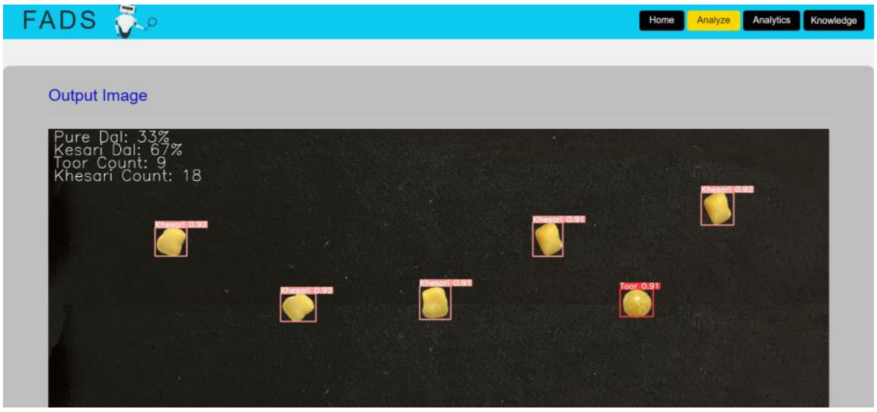

Figure: Flask App Implementation

VI. CONCLUSION

Our food adulteration detection and sorting solution has been designed to address the problem of detecting adulteration in Toor dal, which is crucial for ensuring food safety and security. The solution has been developed through a series of steps, including acquiring a dataset of images of Toor dal, pre-processing the images, creating a dataset, training a CNN model, and evaluating its performance. The resulting model can accurately classify new images of Toor dal as adulterated or non-adulterated, with an accuracy of around 92%, which is a promising result. To implement the solution, we have designed a conveyor belt with a tray for holding the Toor dal samples, along with a mounted camera that captures an image of the batch of dal as it passes through the camera's field of view at regular intervals. The acquired image is then processed to allow the Yolo Dal detection algorithm to predict the type of dal for each individual grain. The resulting output is a labelled image that indicates whether each grain is adulterated or not. The labelled images can be saved locally or on the cloud, depending on the specific requirements of the application.

Our solution is scalable and flexible, making it suitable for deployment across various stages of the food supply chain. By detecting adulterants at an early stage, our solution helps prevent contamination and adulteration from spreading across the supply chain. Additionally, it reduces the workload of food inspectors and quality control teams, who can now focus on more complex tasks.

Overall, we believe that our food adulteration detection and sorting solution provides a valuable solution to the problem of adulteration detection in Toor dal. It has the potential to significantly improve the efficiency and effectiveness of agriculture practices, contributing to building a healthier and more sustainable future for all.

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VII. FUTURE ENHANCEMENTS

The current solution for detecting and sorting grains involves only one low-resolution camera, which may not be sufficient for accurate predictions under varying capture conditions. To address this limitation, the team plans to integrate the solution with a commercial-grade sorting machine that includes a high-resolution camera with a 360-degree field of view and efficient grain sorting techniques.

In addition, the team plans to integrate the solution with blockchain technology to ensure the traceability and transparency of food products and reduce the risk of fraud or adulteration. They also plan to integrate IoT devices for real-time monitoring of environmental factors, improving the overall quality of food products.

The project also has the potential to expand beyond detecting adulteration in grains and can be applied to other food products by training the machine learning algorithms on different datasets. Collaborating with sorting machines solution providers can provide a more comprehensive solution that integrates various aspects of the food supply chain.

Furthermore, the team plans to develop an AI comparison model to compare batches stored in the database to display the precedence of the batches according to the levels of adulteration. The highest levels above the threshold value will be blacklisted and reported to the government. Finally, to improve the overall user experience, the team plans to implement an interactive dashboard facility that incorporates the entire working of the factory for machine alerts and easy access to stored information on batches.

VIII. ACKNOWLEDGEMENT

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