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Automated Apple Disease Classification and Sorting

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Abstract - *Manual sorting and disease detection in post-harvest and yielded agricultural products can be a tedious task for laborers, human prone to fatigue and error. There is thus a need for a low cost, autonomous application to automate the sorting process. This paper presents an Automated fruit classification and sorting system for sorting healthy apples from scab, black rot and apple blotch infected ones. The hardware architecture involves a custom designed 3D-printed conveyor mechanics cluster, driven by L298 N motor controllers and automated servo motors overseen by a Raspberry Pi 3 B. To enable the extraction of reliable features, multi-sensor fusion is used to capture spatial data in real-time from the involved sensors, namely the combined CSI and USB camera feeds. A visual class predictor is also developed on the computer vision platform, i.e. deep neural network with Python's Torch library, that compares the best Convolutional Neural Network (CNN) and Vision transformer (ViT) architecture design choices for accurate classification. To combat the limited processing power of the edge device, a networked Flask & Ngrok client-server environment is developed for remote inference serving. Validations across all supported categories of the system show a 94.8% peak classification accuracy of the best model.*

Key Words: **Automated Sorting, Multi-Sensor Fusion, Vision Transformers, Convolutional Neural Networks, Raspberry Pi.**

1. INTRODUCTION

Agricultural production has been heavily reliant on post-harvest processing technologies that deliver consistent and high-quality produce into the marketplace. For fruit crops in the orchard, a premium apples is determined by overall visual quality and surface fracture characteristics. Apple surface diseases are responsible for a significant net economic loss and result in the deterioration in visual quality, when they are victim to various surface diseases. Citrus fruits too, are susceptible to pests and diseases over the course of their development cycle. Traditionally, manual inspection and sorting algorithms were used, but labor-intensive manual sorting processes whose inherent limitation is labor fatigue, cause long delays, increased cost, and can lead to quality control issues. With the advent of increasingly sophisticated deep learning network architectures such as Convolutional Neural Networks (CNN) and Vision Transformer (ViT), computer vision techniques have gained traction in the agricultural domain for paper, Image classification, and object detection tasks.

While there have been software solutions using deep learning CNNs and ViTs to solve the indirect sorting, classification of diseased produce is computational heavy. Running them on cost-effective edge computing hardware for real-time sorting applications can be a challenge. In this paper, we provide a solution to both these hardware and software challenges that stand in the way of automation for the sorting and grading of fruit in the downstream supply chain.

The hardware solutions we suggest for sorting involves a customized conveyor belt mechanism driven by L298N motor drivers to facilitate sorting by a raspberry pi 3b with two servo motors for mechanical segregation of fruit. The multi-sensor fusion of the system onto the cables by synchronizing their respective cameras is achieved using CSI and USB.

For the software application, the highly computational CNN and ViT deep learning models are hosted on a networked server enabled via the Flask application and Ngrok software, to send real-time image data from the conveyor to a run-time framework in which the ViTS and CNNs are classify the diseased within fruit to a high 94.8% accuracy rate, and send control commands back to the edge raspberry pi controller to perform sorting.

2. LITERATURE REVIEW

1.) Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification, S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, Year 2016. In order to remedy for how manual inspections are time-consuming and have low efficiency and accuracy, computer vision inagriculture have been adopted more. Previous automated inspection methods had difficulties to recognize one such surface abnormality as apple scab, black rot, apple blotch. As pointed out by Sladojevic et al., CNN brought revolutionary improvement to disease classification in applications of diagnostic method in agriculture, because CNN takes CNN as features extracted automatically, and then performs classification with high accuracy, based on registration and organization of spacial information, replacing the old trained models based on machine learning that could not recognized based on the single sensor off-the-shelf digital vision data.

2.) An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale, A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, et al., Year 2021. Building upon the architecture established by convolutional neural networks (CNNs), Vision Transformers (ViT) have shown promise by leveraging self-attention in order to get the entire context of an entire image. Dosovitskiy et al. showed that treating an image as a sequence of patches leads to models with recognition performance that reaches or surpasses that of the best models to date. This is especially useful for automated fruit sorting to pick up on subtle disease symptoms when they appear across the apple as a whole. When used in conjunction with multi-sensor fusion-in which redundant, accurate, high-fidelity spatial data is collected-these new architectures would greatly enhance the robustness of an automated disease classification architecture.

3.) MobileNetV2: Inverted Residuals and Linear Bottlenecks, M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, Year 2018. While state-of-the-art deep learning architectures can reach over 0.99 accuracy, deploying these models on low-cost edge hardware has become a severe computational bottleneck. Sandler et al. highlight the importance of lightweight mobile architectures designed for deployment on edge hardware. Nevertheless, in this complex agriculture setting with mechanical actuation reaching down into the physical world—firing off the L298 full-bridge motor driver in order to actuate the physical conveyor belt and sorting mechanism—running the heavy model directly on a Raspberry Pi is not yet feasible. The system requires the distribution of an inference architecture, which accepts edge sensor-captured data and streams it to a PyTorch backend, allowing the system to actively engage both high-accuracy classification and quick physical actuation.

3. PROPOSED METHOD

Raspberry Pi 3 Model B

The Raspberry Pi 3 Model B serves as the primary edge controller for the physical sorting station. Operating on a Linux-based environment, this single-board computer is responsible for orchestrating all local hardware interactions. It acts as the central bridge between the physical sensors (cameras), the mechanical actuators (motors), and the remote processing server. Because running heavy deep learning models locally on the Pi causes significant latency, its primary role in this proposed system is optimized for data acquisition, secure network transmission, and executing rapid actuation commands.

Multi-Sensor Vision System (CSI & USB Cameras)

To ensure comprehensive feature extraction and mitigate the risk of misclassification due to poor lighting or partial occlusions, the system employs a multi-sensor fusion approach. A synchronized array of both CSI (Camera Serial Interface) and standard USB web cameras is mounted above the conveyor belt. As an apple passes through the inspection zone, these cameras capture high-resolution spatial data from multiple angles, ensuring that localized surface anomalies—such as scab, black rot, or blotch—are fully visible to the classification algorithm.

Conveyor Mechanism & L298N Motor Driver

The transportation of the fruit is handled by a custom-designed, 3D-printed conveyor belt system. The locomotion is powered by DC motors regulated by the L298N Dual Full-Bridge Motor Driver. The L298N acts as an essential interface between the low-voltage logic signals of the Raspberry Pi and the higher current demands of the conveyor motors. This allows the system to smoothly control the speed and pacing of the apples as they enter the camera inspection zone.

Servo Motor Actuation for Sorting

Once a classification decision is made, the physical segregation of the fruit is executed using automated servo motors. Based on the mechanical design modeled in CAD software, custom 3D-printed sweeper arms are attached to the servos. When the Raspberry Pi receives an "infected" or "healthy" signal from the server, it sends a precise PWM (Pulse Width Modulation) signal to the designated servo, actuating the arm to sweep the apple into its respective collection bin.

Networked Communication Server (Flask & Ngrok)

To resolve the computational bottleneck of the Raspberry Pi, a distributed inference architecture was developed. A lightweight Flask web server is deployed to handle the routing of data. Ngrok is utilized to create a secure, stable tunnel from the local edge network to the public internet. The moment the cameras capture an image, the Pi sends this data payload through the Ngrok tunnel to the dedicated processing backend, enabling near real-time communication without requiring a static IP address at the agricultural site.

Deep Learning Classification Backend (PyTorch)

The core intelligence of the system resides on a remote, high-performance computing backend utilizing the PyTorch framework. When the server receives the multi-sensor image data from the Pi, it is fed into the optimized deep learning pipeline. The system compares the performance of advanced Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) to extract features and classify the fruit into distinct categories: healthy, scab, black rot, or blotch. Upon successful classification, the server instantly transmits a lightweight actuation command back through the network to the Raspberry Pi to trigger the servo motors.

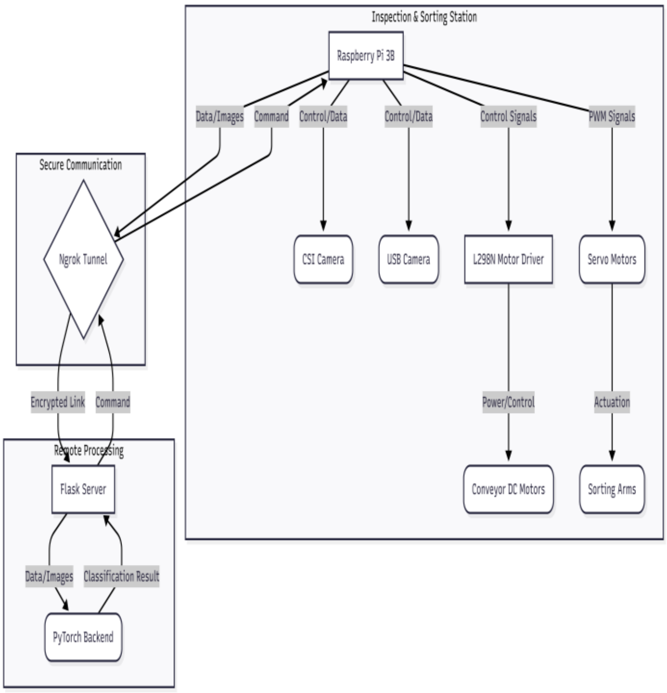

Fig -1: System Architecture Block Diagram

4. WORKING

This automated fruit classification and sorting system works on the principle of continuous visual monitoring and real-time mechanical segregation. When this system is installed on an agricultural grading line, the apples are continuously fed onto a custom 3D-printed conveyor belt whose speed is permanently regulated by an L298N motor driver. The visual sensors, specifically a synchronized array of CSI and USB cameras, are permanently mounted directly above the inspection zone. These cameras act as optical transducers, capturing the complex spatial and color data of the apple's surface and converting the visual anomalies into high-resolution digital image arrays. When the surface characteristics change due to diseases like apple scab, black rot, or blotch, the spatial pixel values in these digital arrays change accordingly. Both camera measurement feeds are instantly received by the Raspberry Pi 3B, which serves as the main intelligent edge controller of this whole physical station.

After receiving these visual arrays, the microcontroller does not process the heavy computations locally to avoid latency; instead, these values are sent toward a remote deep learning system using programmed networking algorithms. The system transmits this data to a dedicated PyTorch processing backend using Flask and an Ngrok secure tunnel. Using this backend model architecture, the system evaluates the fruit using Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) to determine its health status. Once classified, the remote server immediately sends an actuation signal back to the Raspberry Pi, which translates it into an electrical Pulse Width Modulation (PWM) signal. This signal triggers the servo motors, physically sweeping the apple into its respective collection bin.

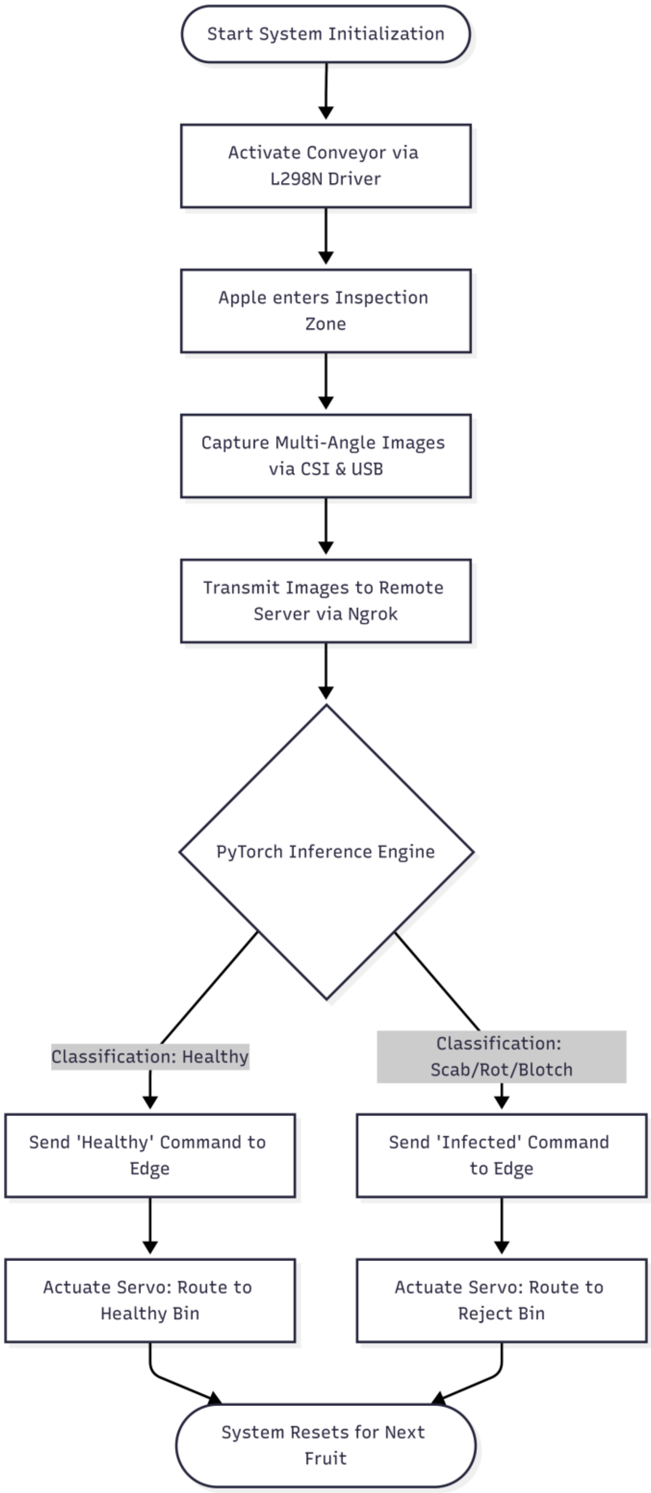

Fig -2: Operational Workflow of the Sorting System

With the development in the computer vision and edge computing industry, single-board computers like the Raspberry Pi and deep learning frameworks have become affordable, have increased processing speeds, and are highly power-efficient. This has led to the increased development of automated embedded systems that the agricultural sector is adopting. The proposed quality control system utilizes these concepts to come up with a system for better economic yield and reduced manual labor for farmers in society. From an engineering perspective, the project has seen concepts acquired through computer science, mechanical design, and embedded systems study periods being practically applied. Mechanical kinematics knowledge was used during the design and 3D fabrication of the conveyor and sweeper arms. Network data flow analysis was used in the secure transmission between the edge controller and the remote server, and advanced machine learning software programming was used during the training of the neural networks to come up with a final finished automated system. The whole classification system, which we have proposed, can be seamlessly integrated into larger industrial grading facilities. This will help agricultural distributors to easily deploy this automated mechanism on existing massive conveyor lines. Advanced edge AI accelerators and programmable logic controllers (PLCs) will greatly come in handy in this regard.

5. CONCLUSIONS

All the project work has been studied, and implemented as fully functional prototype using Raspberry Pi 3 Model B. The programming and remote network routing were done using PyTorch deep learning framework, Flask, and a secure Ngrok tunnel. This demo paper details the design and fabrication of an automated agricultural fruit classification and sorting system.

This project could be an enormous financial leverage for the agricultural sector by improving the efficiency in the filtering and sorting procedure of the harvested fruit for the distributors in farming sector to inspect and examine the quality of the post harvesting produce. The multi-sensor classification system for apple disease detection, achieving a peak accuracy of 94.8%, has been fabricated successfully. In this paper, we demonstrate the crucial and valuable advantages of deploying the distributed edge to server inference for automated agricultural system while drawing its implications for future research direction in the field of agriculture and food industry.

The combining of miniaturized edge controllers with more sophisticated ML models such as Vision Transformers would have the visual impact on farm industry allowing even the most distant packing facility to perform the quality checks to stringent standards minimizing the threat to the market yields. The 3D visual data of the environment can be sampled at a high frame rate in the real-world conveyor or warehouse environment. Moreover, the challenges such as latency, operational time limits on the edge devices and synchronized mechanical actuation were discussed in the paper.

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