AUTOMATIC FRUIT QUALITY DETECTION USING DEEP LEARNING

PROJECT REPORT

Submitted to

the APJ Abdul Kalam Technological University in partial fulfillment of requirements for the award of the Degree of Bachelor of Technology in Electronics and Communication Engineering

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CERTIFICATE

This is to certify that the project titled **AUTOMATIC FRUIT QUALITY DETECTION USING DEEP LEARNING** is the bonafide account of the **ECD 416** presented by **ADITHYAN MANOJ** (MDL21EC009), **ROHITH M S** (MDL21EC099), **RUBEN DAVIS SAJI** (MDL21EC102), **MUHAMMED HADHI V M**(LMDL21EC134) to the APJ Abdul Kalam Technological University in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology in Electronics and Communication Engineering is a bonafide record of the project work carried out by him under my guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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DECLARATION

We hereby declare that the project report **AUTOMATIC FRUIT QUALITY DETECTION USING DEEP LEARNING**, submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under supervision of Ms. Jibi John, Associate Professor, Department of Electronics Engineering

This submission represents our ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources.

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Abstract

In an era where technological innovation meets agricultural sustainability, the proposed project on Automatic Fruit Quality Detection using Deep Learning offers a transformative solution to modern fruit quality analysis. By integrating deep learning models with a conveyor belt system, this project addresses the pressing need for efficient and accurate fruit grading. Utilizing the power of Jetson Nano and cutting-edge image classification techniques, the system can differentiate bananas based on export quality, good, bad, and rotten categories. This automated approach not only enhances the speed and precision of sorting but also ensures minimal human intervention, leading to increased productivity and reduced post-harvest losses. The integration of artificial lighting further optimizes image capture, ensuring consistent accuracy even under challenging conditions. By leveraging machine learning for banana quality detection, the project paves the way for more sustainable and data-driven practices in agriculture. This innovation has the potential to revolutionize the fruit industry, promoting higher quality standards and minimizing waste. Through this endeavor, the aim is to contribute to global agricultural efficiency, fostering a future where technology and sustainability work hand in hand for better crop management and food security.

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List of Abbreviations

CNN - Convolutional Neural Network

GPU - Graphics Processing Unit

GPIO - General Purpose Input/Output

Chapter 1

INTRODUCTION

Bananas are among the most widely consumed fruits in the world, providing a vital source of nutrition and income for millions of people. However, ensuring the consistent quality of bananas throughout the supply chain poses significant challenges. From farms to markets, maintaining high standards is essential to meet consumer expectations and reduce the economic losses caused by poor-quality produce. The global banana trade, which is heavily reliant on export markets, faces growing pressure to deliver fruits that are visually appealing and of excellent quality, while also minimizing waste

One of the major issues in the banana industry is the manual process of sorting and grading. Traditionally, farmers and distributors rely on visual inspection to classify bananas based on their size, ripeness, color, and any visible defects. However, this method is often subjective and can vary greatly depending on individual expertise, leading to inconsistent results and inefficiencies in the supply chain. Moreover, human labor is time-consuming and prone to error, making it difficult to scale operations and meet the demands of larger markets.

1.1 Motivation

The motivation behind developing an automated banana quality classification system is rooted in the increasing need for improved efficiency, consistency, and accuracy in fruit grading, particularly for bananas, a staple crop in the global agricultural industry. Traditional manual sorting methods are inefficient and prone to human error, leading to inconsistencies in quality, delayed processing times, and significant post-

harvest losses that impact farmers and distributors economically. Manual sorting relies on visual inspections to assess ripeness, size, and quality, making it a time-consuming and labor-intensive process, especially for large volumes of bananas. This subjectivity in human judgment results in varying quality standards that negatively affect marketability and consumer satisfaction, while mis-classifications can lead to under- or over-ripened bananas being processed incorrectly, thus increasing waste and reducing profitability. Furthermore, inefficient sorting practices contribute to food waste, which is an environmental concern, as inaccurately classified bananas may spoil prematurely, impacting food security and increasing the carbon footprint associated with agricultural production. Therefore, this project aims to provide a faster, more reliable, and standardized method for assessing fruit quality through automation, enabling precise detection of ripeness, defects, and quality parameters, ensuring that only the best bananas reach consumers. By improving classification accuracy, the system seeks to reduce food waste, enhance supply chain efficiency, and support sustainable agricultural practices, ultimately boosting the productivity of banana producers and the overall quality of bananas in the marketplace while minimizing labor costs and waste to create a more sustainable and profitable banana industry.

1.2 Goal

The aim of the automated banana quality classification system is to provide a fast, reliable, and efficient method for grading bananas based on quality parameters such as ripeness, size, and defects. This system is designed to improve accuracy in quality assessment, reduce human intervention and error, minimize food waste, and ensure consistent grading standards. It aims to be user-friendly, cost-effective, and adaptable for both small-scale farmers and large distributors, ultimately supporting sustainable agricultural practices while enhancing productivity and profitability in the banana supply chain

1.3 Objective

This project aims to develop an Automated Banana Quality Classification System focused on enhancing efficiency, accuracy, and sustainability in the banana supply chain. To ensure precise quality assessment, the system incorporates advanced image processing techniques and machine learning algorithms, utilizing MobileNetV2 for quality classification. These features work together to accurately identify and categorize bananas based on their ripeness and defects, minimizing human error and optimizing the sorting process, thereby creating a more efficient banana handling environment.

For improved operational efficiency, the system also integrates real-time data monitoring and automated sorting mechanisms, enabling seamless tracking of bananas through the classification process. This reduces the time spent on manual inspections and ensures that only high-quality bananas reach consumers, ultimately contributing to reduced food waste and enhanced marketability.

1.4 Scope

The Automated Banana Quality Classification System has a wide scope, making it applicable in various settings such as agricultural processing facilities, distribution centers, and retail environments where efficiency, accuracy, and sustainability are essential. By leveraging advanced machine learning and image processing technologies, the system enables real-time quality assessment and automated sorting, allowing stakeholders to enhance their operations and respond promptly to quality issues. This adaptability increases its value across different stages of the banana supply chain, fostering a more efficient and reliable handling process.

Key features include an intelligent sorting mechanism that MobileNetV2 for qual-

ity classification, allowing for hands-free assessment of banana quality. The system also incorporates real-time data logging and analytics, which monitor and report on quality trends over time, aiding in decision-making for producers and distributors. Additionally, the integration of sustainable practices is emphasized, as the system aims to reduce food waste and improve the overall quality of bananas in the marketplace, supporting a more sustainable agricultural approach.

1.5 Relevance

The Automated Banana Quality Classification System directly addresses the increasing demand for innovative solutions in the agricultural sector that prioritize efficiency and sustainability. By focusing on accurate and automated quality assessment, the system significantly reduces the risks associated with human error in banana sorting, ensuring a reliable process for producers and distributors. This emphasis on accuracy is essential for modern agricultural practices, where technology can play a crucial role in enhancing product quality and marketability.

Efficiency is another key benefit, as the system streamlines the sorting process and minimizes post-harvest losses. With real-time quality monitoring and automated sorting mechanisms, stakeholders can easily manage the classification of bananas, saving time and resources while ensuring that only high-quality fruits reach consumers. This not only helps in reducing food waste but also supports sustainable agricultural practices, contributing to a more resilient and profitable banana industry.

1.6 Novelty

The Automated Banana Quality Classification System uniquely integrates advanced machine learning algorithms and real-time processing capabilities into a single cohesive platform, distinguishing it from traditional manual sorting methods. The use of MobileNetV2 for quality classification allows for precise, hands-free assessment of

banana quality, significantly enhancing both efficiency and accuracy. This feature reduces the reliance on human judgment, minimizing errors and ensuring that only the best bananas are selected for market distribution.

Additionally, the system employs IoT technology to facilitate real-time monitoring and data logging, providing valuable insights into quality trends and operational efficiency. This innovative approach not only streamlines the classification process but also promotes sustainable practices by reducing food waste and improving overall supply chain management. By leveraging these cutting-edge technologies, the system sets a new standard for quality assurance in the banana industry, contributing to a more sustainable and profitable agricultural ecosystem.

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1.7 Applications

The Automated Banana Quality Classification System is designed to deliver significant benefits across various applications within the agricultural sector. In commercial banana production facilities, the system enhances operational efficiency by automating the sorting and grading process. This technology not only reduces labor costs but also minimizes the risk of human error, ensuring that only high-quality bananas reach consumers. By maintaining consistent quality standards, producers can boost their market competitiveness and enhance customer satisfaction.

In retail environments such as supermarkets and grocery stores, the system provides real-time quality assessment, enabling retailers to display and sell bananas that meet consumer expectations. This capability helps reduce food waste and improves inventory management by ensuring that only ripe bananas are sold, ultimately leading to higher sales and reduced losses.

For research and development purposes, the system serves as a valuable tool for agricultural scientists and industry stakeholders interested in studying banana quality dynamics. By analyzing data collected from the classification process, researchers can

gain insights into factors influencing banana quality, such as ripening conditions and storage methods, contributing to advancements in agricultural practices and sustainability.

In conclusion, the Automatic Fruit Quality Detection using Deep Learning addresses the critical need for improved efficiency, accuracy, and sustainability in banana production and distribution. Driven by the aim to enhance quality assurance processes, reduce waste, and streamline operations.The system's goals emphasize providing precise quality assessments, optimizing resource utilization, and contributing to a more sustainable agricultural framework. With its wide-ranging applications, this innovative solution lays the foundation for a smarter, more efficient, and environmentally friendly banana industry.

Chapter 2

LITERATURE REVIEW

This chapter reviews substantial findings and theoretical advancements in banana quality detection using deep learning. The project employ MobileNetV2 for classification, running on a Jetson Nano to enhance accuracy, efficiency, and automation. The following ten papers have been instrumental in shaping our methodology.

Kong, Shihan, Xingyu Chen, Zhengxing Wu, and Junzhi Yu (2023) present a sophisticated method for assessing fruit quality, using CNNs to extract deep image features. Their model emphasizes critical attributes like shape, texture, and color, which are essential for classifying fruit quality. This approach inspired our own feature selection process, particularly for identifying shape deformities, color variations, and surface textures in bananas. Leveraging these insights, we adopted MobileNetV2 for efficient and accurate feature extraction, crucial for our multi-class classification system that operates in real-time on the Jetson Nano. Ojaswini, Rahane, Karan Kumar, and Suresh Jagtap (2020) highlight the benefits of transfer learning in classifying pomegranate growth stages using MobileNet. They demonstrate how pre-trained architectures accelerate training and improve accuracy, a principle that has been central to our project. We applied this approach by using MobileNetV2, which not only reduced our training time but also optimized our model for limited computational resources. Their successful use of transfer learning validated our decision to leverage pre-trained models for banana quality classification, ensuring efficiency without compromising accuracy.

Similarly, Dawood, S., Rahman, M., and Ahmed, A. (2023) introduce a real-time grading system for oil palm, using YOLO for detection and MobileNet for classification. Their emphasis on low-latency performance aligns closely with our system's requirements. Inspired by their methodology, we designed our system to first detect

whether a banana is single or part of a bunch using YOLO, followed by MobileNetV2 for quality classification. Their integration of real-time processing informed our system's design, ensuring it operates efficiently on a Jetson Nano while maintaining high performance. Banerjee, A., Mukherjee, S., Nandi, M., and Dutta, A. (2021) emphasize the importance of image pre-processing techniques, such as normalization and data augmentation, to enhance model robustness. Their methods have been invaluable in our project, where we implemented background optimization and light adjustment to handle varied lighting conditions and banana orientations on the conveyor belt. These pre-processing steps have improved our model's generalization and performance, especially in real-world scenarios.

Shamsuddin, M. A. M., Arshad, M. F. H., and Ibrahim, M. F. H. (2024) discuss the optimization of CNN architectures to balance speed and accuracy in fruit quality detection. Their research highlights the benefits of efficient feature extraction, which influenced our choice of MobileNetV2 for a lightweight yet effective architecture. The study's focus on enhancing real-time classification capabilities directly impacted our approach, ensuring our system remains robust and efficient even when running on a resource-constrained device like the Jetson Nano Further, Abdullah, M. A. A., Mohd Azizudin, N. H., and Endut, A. (2022) focus on using deep neural networks (DNNs) to analyze texture and external surface features. Their work emphasizes key indicators of fruit quality, such as bruises, spots, and color variations. We incorporated their insights into our feature selection, enabling our model to detect subtle yet important visual cues in bananas. The emphasis on texture-based analysis has been crucial for developing a system that can accurately differentiate between various quality categories.

Mohammed, M. N., Al-Zubaidi, Siti Humairah Kamarul Bahrain, and M. Zaenudin (2022) propose a densely connected CNN architecture for improved fruit classification accuracy. They illustrate the benefits of deeper feature layers, which inspired us to consider additional network depth for enhanced performance. However, given our real-time processing constraints, we opted for MobileNetV2's lighter architecture.

This balance between depth and efficiency has been essential for our project, ensuring optimal performance on the Jetson Nano.

Yusuf, M. A., Rahman, H., and Saeed, T. (2021) review pre-processing methods like light adjustment and background optimization to enhance the robustness of fruit quality detection models. We adopted these techniques in our project, creating a controlled image capture environment for consistent and reliable classification. Their emphasis on pre-processing has guided our efforts to manage environmental variations effectively, resulting in a more resilient and accurate model.

Finally, Li, Wen, Zhang, Lei, and Zhao, Jian (2017) explore the challenges of real-time fruit detection in dynamic environments, which are highly relevant to our setup. Their work on optimizing object detection models informed our configuration of YOLO for accurately identifying single bananas and bunches on a moving conveyor belt. Their focus on real-world challenges reinforced the importance of optimizing our model for both precision and speed.

Chapter 3

SYSTEM OVERVIEW

The banana quality classification system is an advanced, automated solution designed to improve the efficiency, consistency, and accuracy of fruit grading in agricultural operations. Leveraging cutting-edge deep learning models,such as MobileNetV2 for quality classification, the system provides a reliable approach to identifying and sorting bananas based on predefined quality categories: export quality, good, bad, and rotten. A high-resolution LG VC23GA camera captures real-time images of bananas as they move along a conveyor belt, ensuring optimal data collection for analysis. The Jetson Nano serves as the system's central processing unit, running the trained models and enabling fast, on-site analysis. The conveyor belt setup facilitates continuous inspection and sorting, while a customized sorting mechanism ensures bananas are categorized accurately and efficiently. Additionally, the system features optimized lighting conditions to maintain consistent image quality, regardless of external factors, thereby enhancing model performance. This comprehensive integration of machine vision, real-time analysis, and automation not only streamlines banana classification but also minimizes human error, reduces food waste, and supports sustainable agricultural practices.

3.1 Block Diagram

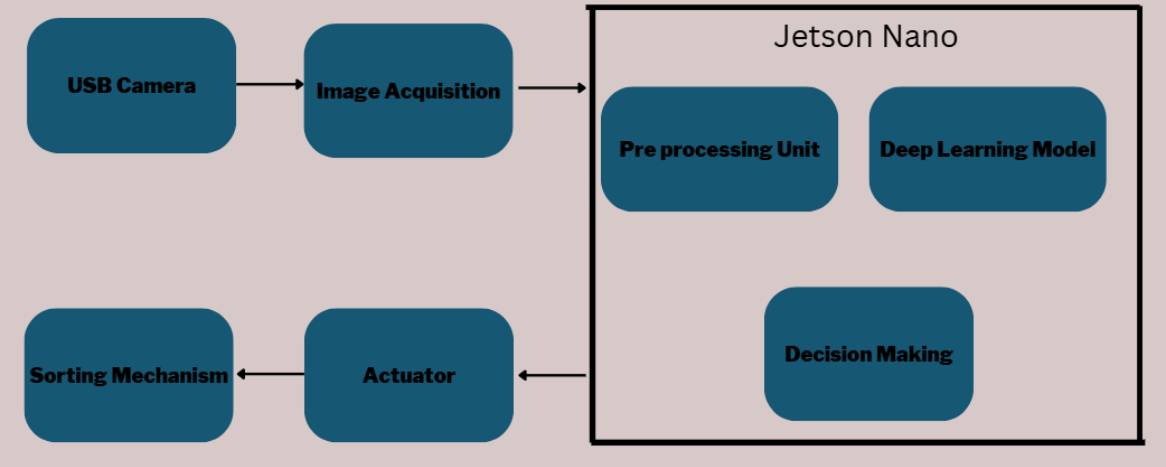

Figure 3.1: System Diagram

The diagram represents a banana quality detection system designed to classify and sort bananas based on their quality. The system uses a USB camera to capture images of bananas as they move along a conveyor belt. These images are then processed and analyzed through a series of steps. The captured images undergo preprocessing to enhance their quality before being fed into a deep learning model, which classifies the bananas as good, medium, or bad. Based on the model's output, a decision-making module activates an actuator and a sorting mechanism to direct the bananas to their respective containers for further processing. This automated system ensures efficient and accurate quality-based sorting of bananas in real time.

3.2 Description of block diagram

1. USB Camera

The USB camera serves as the primary visual sensor of the system, capturing high-resolution images of the bananas as they move along a conveyor belt. It is positioned to ensure a clear view of the bananas, with optimal lighting designed

to reduce shadows and reflections that could interfere with image clarity. This setup is crucial for providing accurate and consistent image data, forming the foundation for the entire classification process. The primary role of the USB camera is to deliver high-quality, real-time visual data, enabling the system to make precise assessments of banana quality. The camera's specifications, such as resolution and frame rate, are carefully selected to support the deep learning model's requirements. Additionally, the continuous image stream facilitates a high throughput of the classification system, making it well-suited for industrial applications.

2. Image Acquisition

The image acquisition block is responsible for collecting and managing images from the USB camera, capturing images at a fixed rate to ensure no banana is missed as it moves along the conveyor belt. It may involve syncing the camera with motion sensors to capture images at precise moments, minimizing the risk of motion blur. Additionally, this block manages data transfer to ensure minimal latency in delivering images to the preprocessing unit, and it may also handle initial filtering to discard corrupted or unusable images, ensuring only quality data is passed on for further analysis. The effectiveness of this stage directly influences the accuracy and speed of the subsequent classification process, making it critical for overall system performance.

3. Preprocessing Unit

The preprocessing unit transforms raw images into a form suitable for analysis by the deep learning model. This involves tasks such as resizing images to a fixed resolution, converting color spaces if necessary, and applying techniques like histogram equalization to enhance contrast. Noise reduction algorithms eliminate unwanted artifacts, and normalization processes ensure uniformity across all

images. To increase model robustness, data augmentation techniques like rotation, flipping, and cropping may be applied, helping the model generalize across variations in banana appearance, such as differences in size, orientation, or background conditions. This stage is vital for standardizing input data, making the deep learning model more efficient and effective.

4. Deep Learning Model

The deep learning model block employs a Convolutional Neural Network (CNN) or a similar architecture to classify bananas into different quality categories. Trained on a large dataset of annotated banana images, the model learns to extract features like texture, color, shape, and surface imperfections. During real-time operation, the model uses these features to make predictions, outputting a classification label for each banana. Techniques such as transfer learning or model optimization are employed to enhance performance and speed. As the core analytical engine, this model is crucial for accurate and reliable quality assessments, balancing complexity and efficiency to ensure high accuracy without excessive computational demands. Its output impacts the sorting mechanism, reducing human error and improving consistency in agricultural quality control.

5. Decision Making

The decision-making block processes the classification output from the deep learning model and determines the appropriate action for each banana. It uses predefined rules to map classification results to sorting actions, such as directing export-quality bananas to a different section from those labeled as bad or rotten. The block may also integrate safety checks to ensure robustness against false positives or negatives and includes mechanisms for handling uncertainties, such as borderline or ambiguous quality cases. Acting as the system's logic center, it translates analytical results into real-world actions, ensuring efficient and ac-

curate operation of the sorting mechanism while seamlessly integrating software intelligence with hardware operations.

6. Actuator

The actuator is a mechanical component that translates electrical signals from the decision-making block into physical movements, involving servo motors, stepper motors, or pneumatic actuators that control sorting gates, conveyor belt speed, or other mechanisms needed to sort the bananas. Designed to be precise and responsive, the actuator ensures accurate and timely sorting actions, essential for a high-speed conveyor system. It must be robust and durable to handle continuous operation, particularly in industrial environments where high throughput is required. Proper synchronization with the decision-making unit ensures that movements are executed without delay, contributing to the system's overall reliability and efficiency.

7. Sorting Mechanism

The sorting mechanism is the final stage where bananas are physically separated based on their classification. This involves automated gates, diverters, or robotic arms that direct bananas into appropriate bins or conveyor lines. It is designed to handle bananas gently, preventing damage during sorting, and may include sensors to confirm successful sorting, providing feedback for error handling or adjustments. A well-designed sorting mechanism minimizes errors and maximizes throughput, which is crucial for large-scale agricultural operations. Its ability to handle high volumes of bananas accurately impacts the system's commercial viability, supporting the project's goal of automating quality control in agriculture and reducing reliance on manual labor while enhancing productivity.

3.3 Feasibility Study

3.3.1 Hardware

Feature	**Jetson Nano**	**Jetson Xavier NX**	**Raspberry Pi 4 + Coral USB Accelerator**
Processor	Quad-core ARM Cortex-A57 CPU, 128-core Maxwell GPU	6-core ARM v8.2 CPU, 384-core Volta GPU, 48 Tensor Cores	Quad-core ARM Cortex-A72 CPU + Edge TPU Accelerator
RAM	4 GB LPDDR4	8 GB or 16 GB LPDDR4x	4 GB or 8 GB LPDDR4 (Raspberry Pi)
Connectivity	Gigabit Ethernet, USB 3.0, GPIO, CSI	Gigabit Ethernet, USB 3.0, PCIe, GPIO, CSI	Gigabit Ethernet, USB 3.0, GPIO
Community & Resources	Strong support from NVIDIA's Jetson community	Strong support, enterprise-level resources	Huge Raspberry Pi community, limited TPU-specific support
Cost-effectiveness	Very cost-effective for basic AI tasks (15600)	High performance-to-cost ratio (116850)	Very cost-effective (94800 for both Pi and Coral USB)

Table 3.1: Detailed list of Processing Units

Feature	**Raspberry Pi Camera Module 3**	**Arducam IMX477 High-Quality Camera**	**LG VC23GA**
Resolution	12 MP (4056 x 3040 pixels)	12.3 MP (4056 x 3040 pixels)	1080p (1920 x 1080 pixels)
Image Quality	High-quality images with HDR and low-light support	High-quality, RAW image capture	Good image quality for video streaming
Frame Rate	1080p at 60 fps, 720p at 120 fps	1080p at 60 fps, lower for higher resolutions	1080p at 30 fps
Interface	MIPI CSI-2 (Compatible with Jetson Nano)	MIPI CSI-2 (Compatible with Jetson Nano)	USB 2.0 (Plug-and-play with Jetson Nano)
Size	25 x 24 x 9 mm	38 x 38 mm	94 x 24 x 29 mm
Cost	2923	8268	3681

Table 3.2: Detailed list of Camera Modules.

3.3.2 Python FrameWorks

Factor	**PyTorch**	**TensorFlow**
Ease of Use	Intuitive, dynamic computation graph, easy debugging	Initially complex, improved with Keras in TF 2.0
Performance	Good for research, optimized GPU acceleration	Highly optimized for production, supports TPUs
Ecosystem & Community	Strong in research, growing industry adoption	Established in production, strong Google-backed support
Deployment Support	TorchScript, ONNX (moderate support)	Extensive (TFX, TF Serving, TF Lite, TF.js)
Research Usage	Preferred in academia	Used but less common
Industry Deployment	Growing adoption	Industry standard for large-scale applications

Table 3.3: Comparison between PyTorch and TensorFlow

3.3.3 Deep Learning Models

Feature	**MobileNetV1**	**MobileNetV2**	**MobileNetV3 Small**
Architecture	Depthwise separable convolutions	Inverted residuals & linear bottleneck	Inverted residuals with squeeze-and-excitation (SE) modules

Accuracy	Lower for the same computational complexity	Higher accuracy for similar computational complexity	Improved accuracy with lightweight architecture
Efficiency	Good for simpler tasks	Better efficiency and performance, especially for complex tasks	Highly efficient for edge devices with minimal computational cost
Use Case	Suitable for general mobile applications	Ideal for mobile and edge applications requiring better accuracy without much increase in resources	Optimized for mobile vision tasks, face detection, and classification
Activation Function	ReLU	ReLU6	Hard-Swish
Feature Extraction	Basic convolutional features	Improved with bottleneck depthwise separable convolutions	Enhanced with SE modules and hard-swish activations
Number of Parameters	4.2M (for 1.0x model)	3.4M (for 1.0x model)	2.9M
Latency	Moderate latency on mobile devices	Lower latency compared to V1	Very low latency with optimized performance
Model Size	17 MB (1.0x)	14 MB (1.0x)	4 MB

Top-1 Accuracy (ImageNet)	70.6%	71.8%	67.4%
Training Complexity	Simple and fast	Slightly complex due to bottlenecks	More complex due to SE modules and hard-swish activations

Table 3.4: Detailed list of Models for Classification

Chapter 4

DESIGN & IMPLEMENTATION

4.1 Hardware Design and Familiarisation

4.1.1 Circuit Diagram

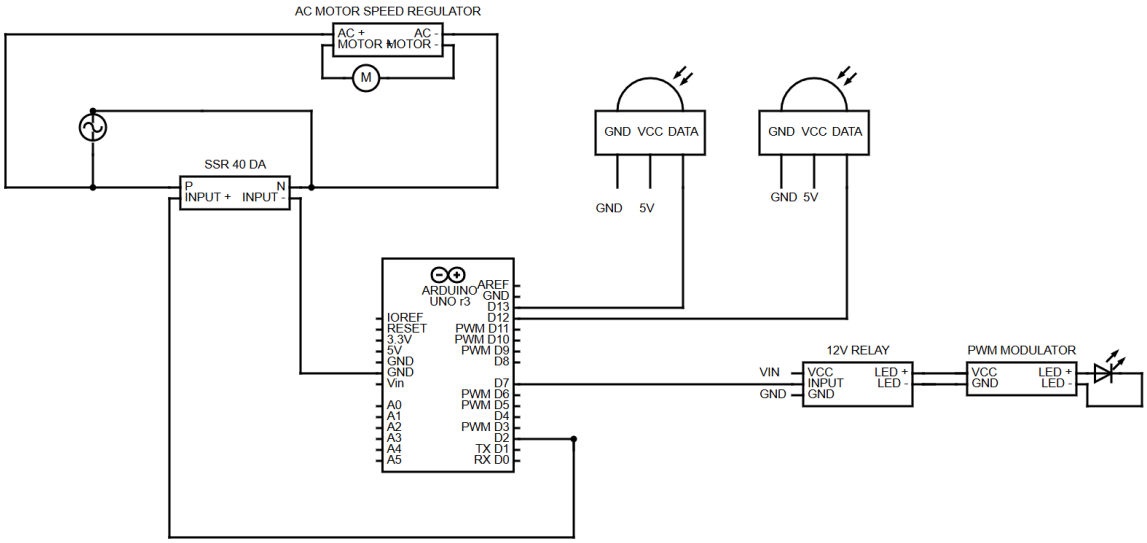

Figure 4.1: First Conveyer Belt System

- **Arduino Uno R3**: Acts as the main microcontroller to control various components.
- **AC Motor and Speed Regulator**: Controls the speed of an AC motor.
- **SSR 40 DA (Solid State Relay)**: Allows the Arduino to switch the AC motor on and off.
- **12V Relay**: Provides additional control for an external load.

- **PWM Modulator**: Generates Pulse Width Modulation (PWM) signals.
- **Sensors**: Two sensors with three connections (VCC, GND, DATA).

The circuit consists of an Arduino Uno R3, which acts as the main microcontroller responsible for controlling various components. It interacts with different modules to manage the operation of an AC motor, sensors, relays, and a PWM modulator.

An AC motor and its speed regulator are included in the setup to control the motor's speed. The speed regulator ensures precise control over the motor's operation based on input signals. To switch the AC motor on and off, an SSR 40 DA solid-state relay is used, which allows the Arduino to manage the motor using digital signals.

A 12V relay is incorporated to provide additional control for an external load. This relay functions as an intermediary switch that can activate or deactivate components depending on the input received from the Arduino. The circuit also includes a PWM modulator, which is responsible for generating Pulse Width Modulation (PWM) signals. These signals are used to regulate various components, including LED circuits.

Two sensors are connected to the system, each having three terminals: VCC, GND, and DATA. These sensors receive power from the Arduino's 5V and GND pins, while their DATA pins are linked to digital input pins on the Arduino, enabling data collection and processing.

The AC motor is connected to an AC motor speed regulator, ensuring smooth operation. The speed regulator is further linked to the SSR 40 DA relay, which is controlled by the Arduino to switch the motor on and off. The two sensors are powered through the Arduino, and their DATA outputs are processed by the microcontroller. A 12V relay is also connected to the Arduino, acting as a control mechanism for the PWM modulator. The PWM modulator ultimately regulates an LED circuit, allowing for controlled lighting operations based on system input.

- **Jetson Nano**: A powerful AI development board used for image processing and control.

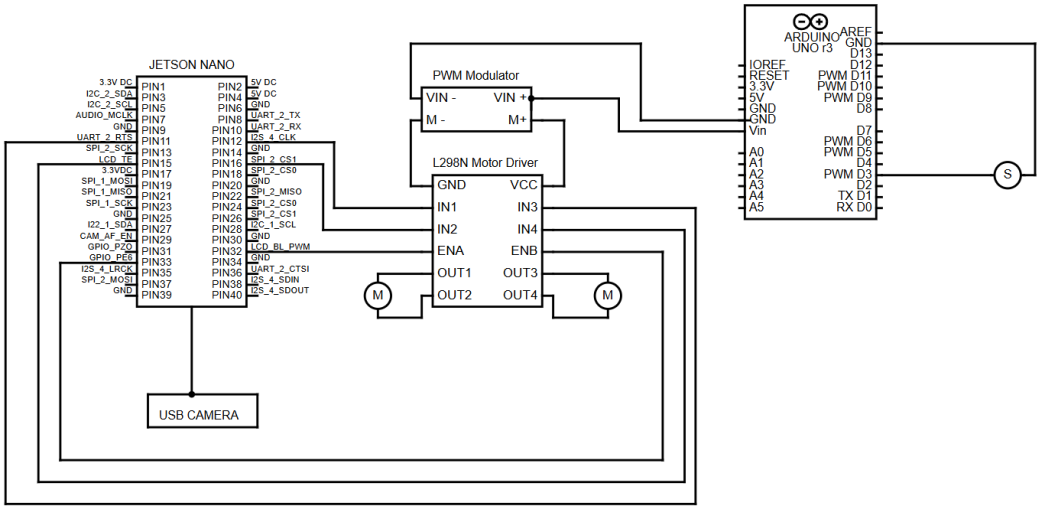

Figure 4.2: Second Conveyer Belt System

- **Arduino Uno R3**: Works alongside Jetson Nano to control peripherals.
- **USB Camera**: Provides real-time image input to the Jetson Nano.
- **L298N Motor Driver**: A dual H-bridge motor driver module that controls DC motors.
- **PWM Modulator**: Used to generate PWM signals for motor control.
- **DC Motor**: Connected to the L298N motor driver for speed and direction control.
- **Sensor (S)**: Connected to the Arduino for additional functionality.

The Jetson Nano connects to a USB camera, enabling real-time video processing for various applications such as object detection, motion tracking, and AI-based analysis. This allows the system to make intelligent decisions based on visual input. The PWM modulator receives control signals from both the Jetson Nano and the Arduino, enabling precise adjustment of output signals for motor speed regulation and other

controlled components. By integrating these two controllers, the system can handle complex automation tasks with efficiency.

The L298N motor driver, which serves as a dual H-bridge motor controller, is powered through the Jetson Nano and is responsible for driving a DC motor. It allows bidirectional control of the motor, adjusting both speed and rotation direction. The motor driver receives control signals from the Jetson Nano, which processes input from the camera and other sensors to determine appropriate motion responses.

Additionally, the Arduino collects input from a sensor and communicates with the Jetson Nano to facilitate synchronized operations within the system. The sensor provides crucial environmental data, such as obstacle detection, temperature, or position feedback, depending on the application. The Arduino processes this data and transmits relevant information to the Jetson Nano, allowing it to make informed decisions for motor control, navigation, or automation processes. Through seamless communication between the Jetson Nano, Arduino, and motor driver, the system ensures efficient and accurate performance across various real-world scenarios.

For the banana quality detection system, we use a 12V power supply, an NVIDIA Jetson Nano Developer Kit for processing, an LG VC23GA camera for high-resolution image capture, and four 12V DC motors for the conveyor belts. A L298N motor driver controls the DC motors, while a PWM speed regulator adjusts the motor speed for precise control. A standard servo motor is employed for the bad banana pushing mechanism, also controlled by PWM for accuracy. Additionally, an IR sensor is included for location analysis, and an LED strip is used for illumination. Jumper wires and connectors facilitate the integration of all components.

4.1.2 Jetson Nano Description

The Jetson Nano is equipped with a versatile range of ports that make it highly functional for various computing and interfacing needs. It features a **USB Type-C**

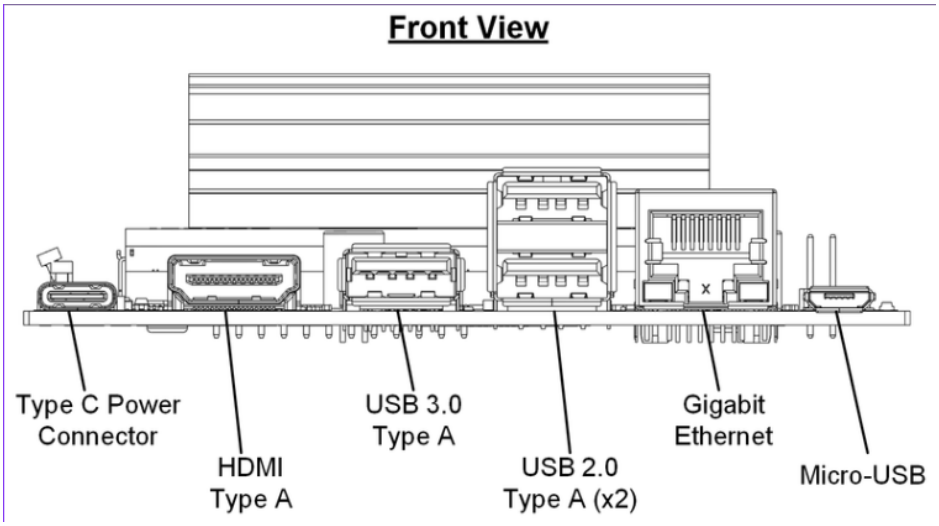

Figure 4.3: Front View of Jetson Nano

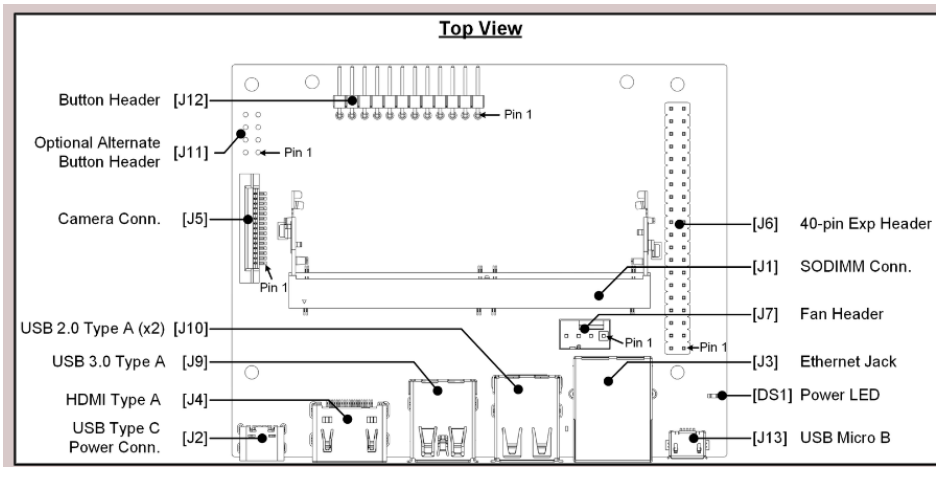

Figure 4.4: Top View of Jetson Nano

power connector [**J2**], which is primarily used to power the device. This USB-C port is known for its flexibility, as it can handle both power delivery and data transfer. For video output, the Jetson Nano includes an **HDMI Type A port** [**J4**], allowing users to connect the device to an external display, such as a monitor or TV, for high-definition video output.

In terms of data transfer, the device has several **USB ports**. There is a **USB 3.0 Type-A port** [**J9**], offering faster data transfer rates compared to USB 2.0, making it suitable for connecting high-speed peripherals like external drives or cameras. Additionally, the board includes **two USB 2.0 Type-A ports** [**J10**], which, although slower than USB 3.0, are widely compatible with many devices, such as keyboards, mice, flash drives, and other accessories. A **Micro-USB port** [**J13**] is also present, typically used for debugging or connecting the device to other systems.

The **Gigabit Ethernet port** [**J3**] allows the Jetson Nano to connect to a network via an Ethernet cable, offering a stable and high-speed internet connection, which can be advantageous for applications requiring reliable network access. Another key connectivity feature is the **40-pin expansion header** [**J6**], providing access to GPIO (General Purpose Input/Output) pins, as well as other interfaces. This makes it possible to connect various sensors, modules, and custom electronics, expanding the Jetson Nano's capabilities in embedded system projects.

The board is also designed for specific components like a camera, with a **camera connector** [**J5**] that allows users to attach a camera module for computer vision applications. A **SODIMM connector** [**J1**] is available for adding memory modules, enhancing the device's RAM to accommodate more demanding tasks. To prevent overheating during intensive operations, there is a **fan header** [**J7**] for attaching a fan to cool the system.

Other important connectors include additional **USB 3.0 Type-A** [**J9**] and **USB 2.0 Type-A** [**J10**] ports, providing more options for peripheral connections. A **power LED** [**DS1**] serves as a visual indicator of the device's power status, while the **USB**

Micro-B connector [**J13**] offers additional data transfer or debugging functionality. For users needing physical buttons, there are **button headers** [**J12**] for connecting control or reset buttons, as well as an **optional alternate button header** [**J11**] for customized functions.

Overall, the Jetson Nano's comprehensive selection of ports makes it highly adaptable for various applications in AI, IoT, and embedded systems development.

4.1.3 Environment Setup of Jetson Nano

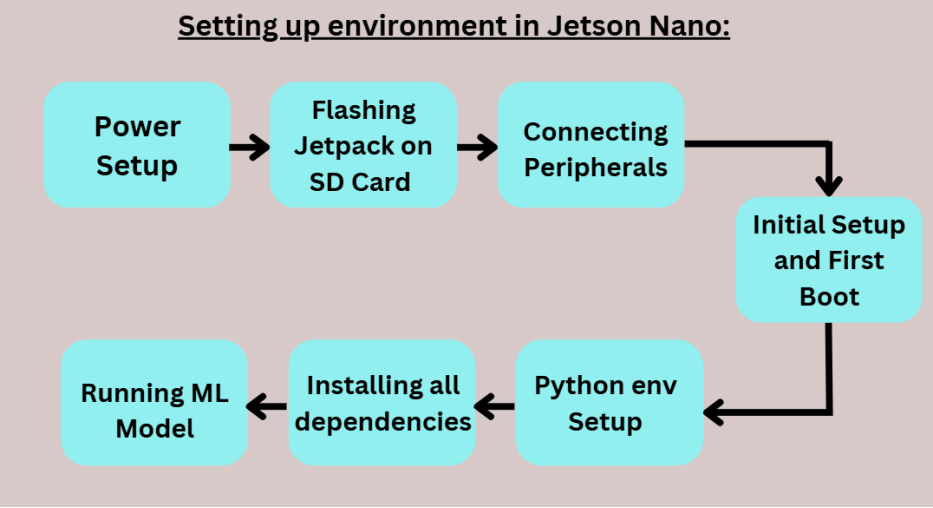

Figure 4.5: Environment setup Block Diagram

To set up the Jetson development environment, begin by gathering the necessary hardware, including an HDMI cable, monitor, keyboard, and mouse, which you'll need to interface with the Jetson device. Next, download JetPack 4.6.1, NVIDIA's software package that includes drivers, libraries, and tools for Jetson platforms. Install the NVIDIA SDK Manager on your host machine, as it will help you flash JetPack onto the Jetson device and manage development resources.

Using the SDK Manager, flash JetPack onto an SD card, which will serve as the Jetson's bootable storage, containing the operating system and essential libraries. Then, set up the Jetson hardware by connecting it to power and peripherals, and

insert the flashed SD card. Power on the Jetson device, and follow the on-screen instructions to complete the initial configuration, including user account setup, passwords, and network connection.

Once the initial setup is complete, install any additional dependencies, such as software packages, drivers, or libraries needed for your specific applications. Test the installation to confirm that JetPack and other dependencies are functioning correctly. Configure the development environment according to your project's needs, which might involve setting environment variables, installing an IDE, or configuring software tools. Set up a Python environment on the Jetson device by installing Python and essential libraries like NumPy, OpenCV, or TensorFlow if required. With the setup complete, you're ready to begin developing on the Jetson platform, deploying code, and testing applications.

4.1.4 Deploying ML Model in Jetson Nano

To begin setting up the Jetson development environment, you need to gather the necessary materials, such as an HDMI cable, monitor, keyboard, and mouse, which are required to interface with the device. The first software step is to download **JetPack 4.6.1**, NVIDIA's development kit that includes drivers, libraries, and tools for the Jetson platform. Next, install the **NVIDIA SDK Manager** on your host machine, which will be used to flash the JetPack software onto an SD card. This SD card will serve as the bootable storage for the Jetson device, containing the operating system and essential libraries. After flashing the SD card, proceed with the initial hardware setup by connecting the Jetson device to power and peripherals, and inserting the SD card. Power on the Jetson and follow the on-screen instructions to complete the initial configuration, such as setting up user accounts and network connections. Once the setup is done, install any additional dependencies or software packages that may be required for your specific project or development needs. To verify that the installation was successful, run tests to ensure that JetPack and all necessary dependencies are

functioning properly. After this, configure the development environment according to your project's requirements, which may include setting up environment variables or installing software tools. Additionally, set up a **Python environment** by installing Python and any necessary libraries like NumPy, OpenCV, or TensorFlow. Once everything is configured, you can begin developing, deploying code, and testing applications on the Jetson platform.

4.1.5 CUDA Processing in Jetson Nano

CUDA enables the Jetson platform to harness the power of its GPU cores for parallel processing, significantly accelerating data-intensive tasks compared to using a CPU alone. This is particularly important for deep learning workloads, where large datasets and complex models are processed in parallel. Jetson devices support the **CUDA Toolkit**, which includes optimized libraries such as **cuDNN** for neural networks and **cuBLAS** for linear algebra. These libraries allow developers to accelerate AI and machine learning tasks without the need for writing low-level GPU code. The **JetPack SDK** further enhances development by providing a comprehensive software suite, including CUDA, cuDNN, TensorRT, and other essential tools. JetPack simplifies the setup of a development environment, enabling developers to build CUDA-accelerated applications with ease. Moreover, CUDA's integration with Jetson facilitates **low-latency edge computing**, allowing AI models to run directly on the device without relying on cloud computing. This reduces latency and enables real-time processing, which is critical for edge applications such as autonomous robots, drones, and smart cameras that require instant decision-making.

4.1.6 TensorRT Optimization in Jetson Nano

TensorRT is an advanced deep learning inference optimizer and runtime library developed by NVIDIA. It is specifically designed to enhance the performance of neural network models on NVIDIA GPUs, including the Jetson Nano. TensorRT optimizes

neural network models by performing various techniques such as precision calibration, kernel fusion, and layer aggregation. These optimizations reduce latency and increase throughput, making it highly suitable for real-time applications.

One of the key advantages of using TensorRT on the Jetson Nano is its ability to leverage mixed-precision computation, where lower-precision (FP16 or INT8) arithmetic is used without significantly compromising accuracy. This drastically improves inference speed while minimizing computational load and memory usage. TensorRT also provides support for popular deep learning frameworks like TensorFlow and PyTorch through model conversion to ONNX format. This seamless integration allows developers to convert pre-trained models and directly deploy them on the Jetson platform.

By incorporating TensorRT into the deployment pipeline, developers can achieve optimal utilization of the Jetson Nano's GPU resources, enabling efficient execution of complex AI models. The combination of CUDA and TensorRT provides a powerful toolchain for building high-performance edge AI applications, such as object detection, image classification, and real-time video analytics.

4.1.7 Specifications and familiarisation of hardware

NVIDIA Jetson Nano

The NVIDIA Jetson Nano is a compact, powerful AI computing platform tailored for edge devices and embedded systems. Equipped with 4 GB of LPDDR4 RAM, it operates at a 5V supply with a minimum current requirement of 2A, making it efficient for power-limited environments. The Jetson Nano features a quad-core ARM Cortex-A57 CPU alongside a 128-core Maxwell GPU, both of which contribute to its robust performance for deep learning, computer vision, and other AI-related tasks. It supports a variety of machine learning frameworks, allowing developers to easily implement diverse AI models. For storage, it includes a microSD card slot, providing flexible capacity options. Additionally, the platform offers extensive connectivity, in-

cluding USB 3.0, HDMI, and Gigabit Ethernet, facilitating seamless integration with a wide range of peripherals and networks. Its small form factor and low power requirements make the Jetson Nano an ideal choice for applications such as robotics, drones, and smart devices, where real-time AI processing is needed in constrained environments.

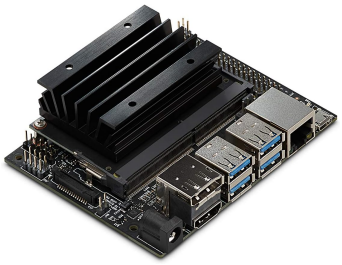

Figure 4.6: Jetson nano

12V DC Gear Motor

The 12V DC gear motor is a powerful and versatile motor designed to cater to applications that require both reliable torque and speed control under varying load conditions. It incorporates a precision-engineered gearbox that reduces the speed of the motor while significantly increasing its torque output. This design ensures the motor can handle tasks that involve pushing or pulling heavy loads, such as driving conveyor belts in industrial automation, powering robotic arms, or controlling mechanisms in automated systems. With a holding torque of 4 kg-cm, the motor can securely hold its position under load without slipping, which is crucial for precise positioning and handling.

Operating at a rated voltage of 12V, this motor is both energy-efficient and easy to power from common DC sources. It runs with a no-load speed of 200 RPM, providing a balance between speed and torque suitable for applications where controlled, moderate movement is needed. The motor's compact form factor allows for easy integration into confined spaces, making it ideal for both portable systems and stationary machinery.

Its operational efficiency minimizes heat generation, prolonging motor life and reducing the need for cooling solutions, which is particularly advantageous in industrial settings.

This gear motor is built with durability in mind, featuring high-quality materials that ensure longevity and consistent performance even under extended use. It is highly adaptable and can be fitted with various accessories like mounting brackets, pulleys, or belts to extend its utility across a wide range of tasks. Whether in hobbyist setups or industrial environments, this 12V DC gear motor serves as a reliable, flexible solution for automation tasks requiring stable torque and speed, contributing to efficient and streamlined operation.

Figure 4.7: DC Gear Motor

Camera: LG VC23GA

The LG VC23GA is a premium camera solution known for its high resolution, versatility, and reliability across a range of imaging applications. Boasting Full HD (1080p) video, making it an excellent choice for tasks requiring precise visual detail, such as in robotics, computer vision, machine learning, and automated quality inspection systems. The camera's compact, durable design allows for seamless integration into a variety of setups, from industrial automation to academic research, and its superior image processing capabilities support both indoor and outdoor deployments.

One of the standout features of the LG VC23GA is its advanced low-light performance, enabling accurate image capture even in suboptimal lighting conditions, which is particularly valuable for nighttime surveillance, remote monitoring, and controlled lab environments. Its wide field of view supports extensive coverage in single-frame shots, ideal for capturing broader perspectives without sacrificing image quality, making it suitable for monitoring and analysis in IoT systems and AI-driven applications. The camera's adaptive exposure and focus capabilities further enhance its usability in dynamic or fast-changing scenarios, ensuring that it consistently delivers high-quality images that are essential for machine learning algorithms, object recognition, and precise visual data analysis. Overall, the LG VC23GA is engineered to support a broad spectrum of applications where high-resolution imaging and reliable performance are crucial.

Figure 4.8: LG USB Camera

E18-D80NK - Infrared Proximity Sensor

The E18-D80NK Infrared Proximity Sensor is an efficient and compact electronic device designed for non-contact object detection. It operates at a voltage range of 5V to 12V DC, making it versatile for various applications. The sensor consumes low power while offering stable and accurate proximity detection with a sensing distance adjustable between 3 cm to 80 cm. Its infrared emitter and phototransistor receiver work together to detect reflected IR radiation from objects, allowing reliable distance measurement and object presence detection.

This sensor is equipped with a built-in potentiometer for easy distance adjustment, enabling fine-tuning based on specific requirements. The output signal is digital (high/low), making it compatible with microcontrollers and other digital circuits. With its fast response time and excellent ambient light immunity, the E18-D80NK performs well in both indoor and outdoor environments, including challenging lighting conditions.

Figure 4.9: E18-D80NK - Infrared Proximity Sensor

L298N Motor Driver

The L298N is a robust dual H-bridge motor driver module tailored for controlling DC and stepper motors, making it ideal for diverse applications in robotics, automa-

tion, and DIY electronics projects. Operating within a wide voltage range of 5V to 35V, this motor driver provides a maximum output current of 2A per channel and can handle up to 25W of power. This capacity makes it well-suited for managing small to medium-sized motors, enabling precise bidirectional control of two motors simultaneously. Additionally, the L298N integrates Pulse Width Modulation (PWM) functionality, allowing for efficient speed control and smooth motor operation.

The L298N driver includes essential safety features such as thermal shutdown and overcurrent protection, which help maintain stable performance even under demanding conditions. Its dual H-bridge configuration allows it to control each motor independently, facilitating more versatile motion control and supporting applications that require coordinated movement, like wheeled robots and conveyor systems. The module's versatility, durability, and ease of use make it a popular choice for both hobbyists and professionals, enabling controlled and reliable motor operation in projects requiring consistent performance and precision.

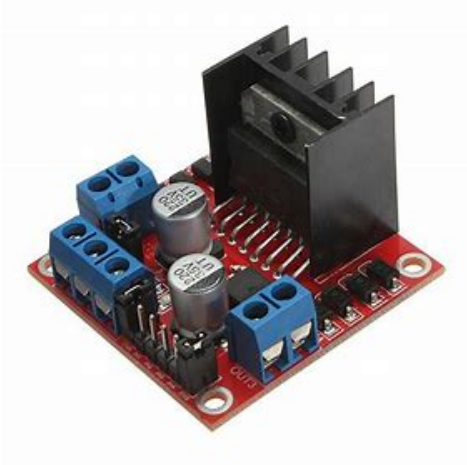

Figure 4.10: L298N Driver Module

PWM DC Motor Speed Controller

The PWM DC motor speed controller is a highly efficient device designed to manage the speed of DC motors through the use of pulse width modulation (PWM) techniques.

Operating within an input voltage range of 6V to 24V, this controller is versatile and compatible with a wide array of motor types and sizes, making it a valuable component in various applications. It is capable of handling input currents of up to 10A, which allows it to cater to medium to high-power applications effectively.

By adjusting the duty cycle of the PWM signal, the controller enables precise speed control, facilitating smooth acceleration and deceleration of connected motors. This capability is essential in applications such as robotics, electric vehicles, conveyor systems, and other automation projects, where variable speed control is crucial for optimizing performance and efficiency. Furthermore, the PWM DC motor speed controller is equipped with essential safety features, including thermal protection and overcurrent protection. These features ensure safe and reliable operation, particularly during extended use or under heavy loads, safeguarding both the controller and the connected motors from potential damage. With its combination of flexibility, efficiency, and safety, the PWM DC motor speed controller is an ideal choice for enhancing motor control in diverse engineering and automation tasks.

Figure 4.11: PWM Motor Speed Contoller

OLED Display

The OLED display is a compact and versatile screen that finds extensive use in embedded systems and Internet of Things (IoT) applications. It is available in two popular sizes, 0.96-inch and 1.3-inch, both of which feature a resolution of 128x64 pixels. This resolution allows for clear and vibrant visuals, making it suitable for a variety of display needs. Utilizing organic light-emitting diode technology, the OLED display offers high contrast ratios and exceptional color reproduction while maintaining low power consumption.

The display can connect through I2C or SPI interfaces, ensuring easy integration with a wide range of microcontrollers, including the Raspberry Pi and Jetson Nano, which are often used in advanced projects. This display excels in providing real-time feedback in applications such as robotics, automation systems, and monitoring dashboards, where displaying critical status information or data is essential for effective operation. Its lightweight and compact design make it ideal for a diverse range of projects, allowing designers and engineers to incorporate an efficient and visually appealing output solution without occupying much space. Moreover, the ability to display graphics and text dynamically enhances user interaction, making the OLED display a favored choice in modern technology applications that demand both performance and aesthetic appeal.

Figure 4.12: OLED Display

Buzzer

A buzzer is an electromechanical device designed to produce sound, commonly used in a variety of electronic applications for signaling or alerting purposes. Operating at a voltage of 5V and drawing a maximum current of 20mA, buzzers are highly efficient components in embedded systems. There are two main types of buzzers: active and passive. An active buzzer generates sound when a DC voltage is applied directly, thanks to an internal oscillator that allows it to produce sound continuously without requiring any additional circuitry. This makes active buzzers easy to implement, as they only need a simple on/off signal to operate. In contrast, a passive buzzer relies on an external signal to create sound; it generates noise when an AC signal or square wave is applied, with the frequency of the signal determining the pitch of the sound produced. This allows for more versatile sound generation, including melodies, as the user can modulate the input signal. Buzzers are widely used in alarms, timers, and notification systems, providing auditory feedback in various electronic devices. Their compact size and low power consumption make them ideal for use in battery-powered applications and small electronic projects.

Figure 4.13: Buzzer

Servo Motor- MG996R

The MG996R is a high-torque servo motor widely used in robotics, automation, and remote-controlled devices. Designed to operate within a voltage range of 4.8V to 6.6V, this servo motor is equipped with a metal gear mechanism that significantly enhances its durability, allowing it to withstand more stress and provide greater torque output compared to plastic gear servos. With a torque rating of approximately 9.4 kg-cm when operating at 6V, the MG996R is capable of effectively handling demanding applications that require precise movement and control, such as robotic arms, steering mechanisms in RC vehicles, and various automated systems. Its 180-degree rotation capability allows for a broad range of motion, making it suitable for tasks that require angular positioning. Additionally, the MG996R features a high-speed response, which is essential for applications that require rapid actuation. The servo motor is equipped with advanced feedback mechanisms that enable it to maintain its position accurately, ensuring reliability and precision in its operations. Its robust construction and versatile performance make the MG996R a popular choice among hobbyists and professionals alike, enabling the development of complex and dynamic robotic systems.

Figure 4.14: Servo Motor

LED Strip

The LED strip is a versatile and flexible lighting solution commonly used in decorative lighting, signage, and automation projects. Available in both RGB (multicolor) and single-color variants, these strips cater to a wide range of applications across various environments. Operating at a voltage of 12V, they deliver bright and vibrant illumination while maintaining low power consumption, making them energy-efficient options for both residential and commercial use. Each strip typically comprises multiple LEDs spaced along a flexible circuit board, which allows for easy installation and customization to fit different spaces and designs. Furthermore, LED strips can be controlled using Pulse Width Modulation (PWM), enabling smooth dimming and color mixing, which is ideal for creating dynamic lighting effects in homes, events, and creative installations. Their adhesive backing simplifies the mounting process on a variety of surfaces, ensuring a secure fit and enhancing the aesthetic appeal of any space. With their durability and adaptability, LED strips are suitable for a myriad of applications, including ambient lighting, accent lighting, backlighting, and even in complex automation systems where programmable lighting is essential. Whether used indoors or outdoors, LED strips provide an effective and visually appealing lighting solution that can transform any area into an illuminated masterpiece.

Figure 4.15: LED Strip

Arduino Uno

The Arduino Uno is a popular microcontroller board based on the ATmega328P. It operates at a voltage range of 7-12V and provides an output voltage of 0-5V, with a maximum current of 500mA. The board features 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz quartz crystal, a USB connection, a power jack, an ICSP header, and a reset button. It is well-suited for both beginners and advanced users due to its ease of use and extensive community support.

The board can be powered via a USB connection or an external power source. It also features built-in voltage regulation and can communicate with a computer or other devices via the USB interface. Programming is done using the Arduino IDE, which supports C and C++ with built-in libraries to simplify coding. The Uno is ideal for various embedded systems and DIY projects, such as robotics, home automation, and data acquisition systems.

Figure 4.16: Arduino Uno Board

4.2 Deep Learning Model Design

The machine learning model used in this project is MobileNetV2, a lightweight and efficient convolutional neural network (CNN) architecture optimized for mobile and edge devices. MobileNetV2 was pre-trained on ImageNet—a large-scale dataset with thousands of images—and then fine-tuned to classify bananas into four quality categories: good, bad, and medium. This transfer learning approach allows the model to leverage previously learned visual features and adapt them to recognize specific characteristics of bananas, such as color, texture, and shape, with high accuracy. By balancing computational efficiency and performance, MobileNetV2 enables the banana quality classification system to perform real-time analysis on a low-power device like the Jetson Nano, making it an ideal choice for agricultural automation and embedded AI applications.

4.2.1 Algorithm for ML model

Step 1: Initialize necessary libraries (TensorFlow, Keras, etc.).

In this initial step, it is essential to initialize the necessary libraries required for the project. This typically includes importing libraries such as PyTorch and Torchvision, which are fundamental for constructing and training deep learning models. By ensuring these libraries are properly set up, you create a solid foundation for the subsequent steps in the model development process.

Step 2: Organize the dataset into the following directories:

```
/dataset/train/good/
/dataset/train/bad/
/dataset/train/intermediate/
/dataset/validation/good/
/dataset/validation/bad/
/dataset/validation/intermediate/
```

Step 3: Preprocess the dataset:

To prepare the dataset for training and validation, ImageDataGenerators are created to streamline the process of loading and augmenting the images. These generators not only facilitate the efficient management of the dataset but also enhance the training data through data augmentation techniques. Data augmentation involves applying various transformations such as rotation, scaling, and flipping to the training images, thereby increasing the diversity of the dataset. This process helps the model generalize better by exposing it to a wider range of variations during training.

Step 4: Load the pre-trained MobileNetV2 model:

To begin constructing the classification model, the MobileNetV2 architecture, which has been pre-trained on the ImageNet dataset, is loaded with the parameter `include_top=False`. This configuration allows the model to leverage the powerful feature extraction capabilities of MobileNetV2 while omitting the final classification layers, which are specific to ImageNet. Following this, the layers of the base model are frozen, preventing their weights from being updated during the initial training phases. This approach helps to retain the learned features from the pre-trained model, allowing the new model to focus on training the added layers for the specific task of banana classification without altering the foundational representations learned from the broader dataset.

Step 5: Build the model:

After loading the pre-trained MobileNetV2 model and freezing its base layers, the next step involves building the new model architecture. A GlobalAveragePooling2D layer is added immediately following the base model, which serves to reduce the spatial dimensions of the feature maps while maintaining the essential information necessary for classification. This is

followed by the inclusion of a fully connected layer, specified as `Dense(128, activation='relu')`, which introduces non-linearity and allows the model to learn complex patterns in the data. Finally, the output layer is configured as `Dense(4, activation='softmax')`, designed to classify the input images into four distinct categories relevant to the banana classification task. This output layer utilizes the softmax activation function to produce probability distributions across the defined classes, facilitating the selection of the most probable category for each input image.

Step 6: Compile the model:

In the model compilation stage, the optimizer is set to Adam with a learning rate of 0.0001, which is a popular choice for many deep learning applications due to its adaptive learning rate capabilities that help accelerate the training process. The loss function used is `categorical_crossentropy`, which is appropriate for multi-class classification problems as it quantifies the difference between the predicted probability distribution and the actual distribution of classes. To evaluate the model's performance during training, the accuracy metric is employed, providing a straightforward indication of how well the model is performing by measuring the proportion of correctly classified instances over the total number of instances.

Step 7: Train the model:

To train the model, the first action is to fit it on the training data using the `train_generator`, which provides the augmented images in batches. This process involves using the training dataset to enable the model to learn the underlying patterns and features associated with each class. Concurrently, the model is validated using the validation data supplied by the `val_generator`, allowing for real-time assessment of its performance on unseen data during training. The training is conducted over a specified number

of epochs, typically set to 10 in this case, which represents the number of complete passes through the entire training dataset. This step is essential for optimizing the model's weights and biases, ultimately enhancing its accuracy and predictive capabilities.

Step 8: Fine-tune the model:

During the training phase, the model is fitted on the training data using the `train_generator`, which efficiently loads batches of images for training. This generator ensures that the model is exposed to the training dataset iteratively, allowing it to learn the patterns and features necessary for classification. After fitting the model, it is validated using the validation data provided by the `val_generator`, which serves as an independent dataset to assess the model's performance and generalization capabilities. The training process is carried out for a specified number of epochs, in this case, 10 epochs, allowing sufficient time for the model to converge and refine its weights based on the training data.

Step 9: Evaluate the model on the validation data:

After training the model, the next step involves evaluating its performance on the validation data. This is achieved by calculating the validation accuracy and loss, which provide insights into how well the model generalizes to unseen data. The validation accuracy indicates the proportion of correctly classified instances out of the total validation samples, while the validation loss quantifies the difference between the predicted and actual outcomes. These metrics are crucial for assessing the effectiveness of the model and identifying any potential overfitting or underfitting issues that may need to be addressed in subsequent training iterations.

Step 10: Save the trained model:

To save the trained model, it is essential to serialize the model architecture, weights, and training configuration to a file. This allows for easy reloading and utilization of the model in future applications without needing to retrain it from scratch. In PyTorch, the model can be saved in various formats, such as saving only the model's state dictionary (.pt or .pth format) or the entire model using torch.save(), depending on the specific requirements for deployment or further experimentation.

Step 11: Plot training and validation accuracy/loss over epochs:

After training, it is important to visualize the training and validation accuracy and loss over epochs. This is accomplished by plotting graphs that depict how the model's performance evolves throughout the training process. Such plots provide valuable insights into the model's learning dynamics, allowing for the identification of potential issues such as overfitting or underfitting. By analyzing these metrics, adjustments can be made to the training process or model architecture to enhance performance.

Step 12: Initialize hardware (camera):

Initializing the hardware, specifically the camera, is a crucial step in preparing for real-time inference. This involves setting up the camera parameters and ensuring it is properly configured to capture images or video feed for classification tasks. Proper initialization allows for seamless integration of the hardware with the trained model, enabling efficient data acquisition for the classification process.

Step 13: Model Selection:

Experimented different deep learning models which include mobileNetV1, MobileNetV2 and mobileNetV3. Among the three mobileNetV2 has been

selected as an ideal deep learning model for its accuracy and smooth deployment on edge devices like jetson nano

Step 14: Load the pre-trained MobileNetV2 model:

Loading the pre-trained MobileNetV2 model is the final step in the process, where the previously trained model is brought into the current environment for inference. This step involves importing the model architecture and weights, ensuring that it is ready to make predictions on new data. By loading the model, users can leverage its learned features and apply it to real-time classification tasks, benefiting from the training that has already been performed.

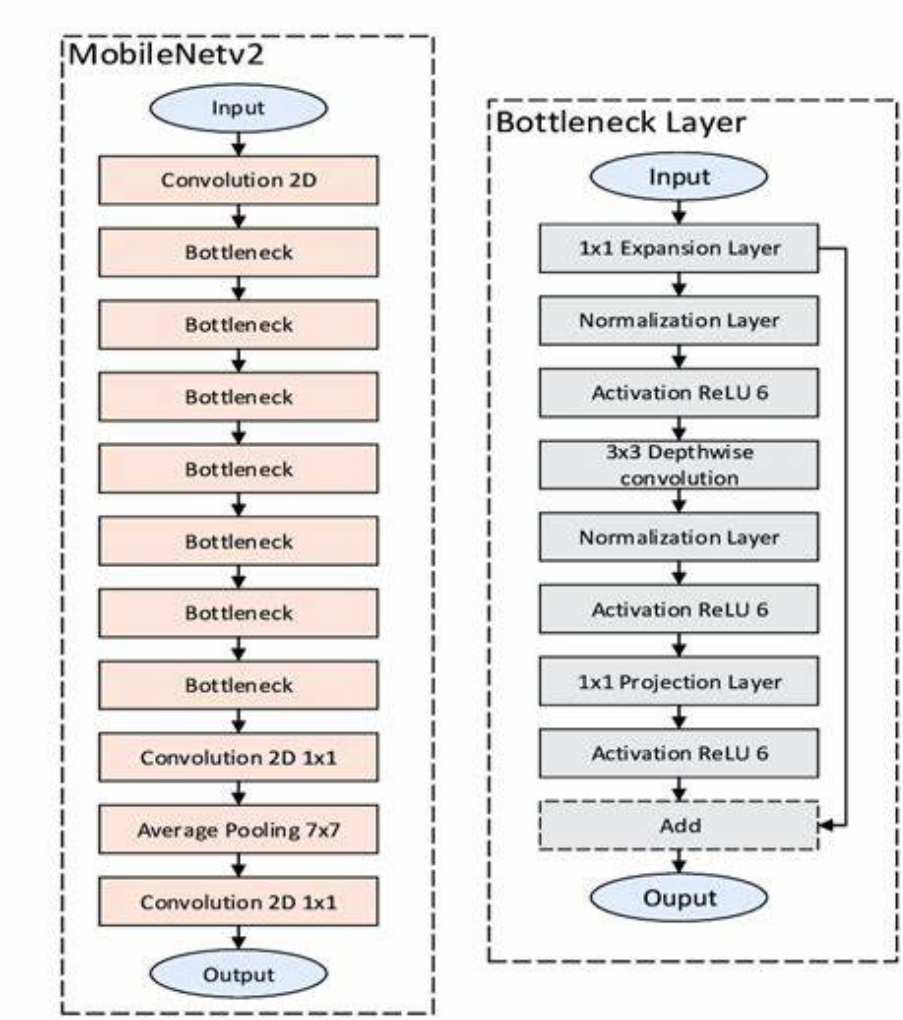

Figure 4.17: Architecture of MobileNetV2

4.2.2 Familiarization of software

1.Jupyter Notebook

Jupyter Notebook is an open-source web application that allows users to create and share documents containing live code, equations, visualizations, and narrative text. It supports various programming languages, including Python, R, and Julia, making it a versatile tool for data analysis, scientific research, machine learning, and educational purposes. Jupyter's interactive interface enables users to run code in small chunks, visualize results in real time, and document their workflow seamlessly within a single document. This combination of code execution and rich text support encourages collaboration and reproducibility, making Jupyter Notebook a popular choice among data scientists, researchers, and educators for developing and presenting complex analyses and visualizations.

2.Visual Studio Code

Visual Studio Code (VS Code) is a lightweight, open-source code editor developed by Microsoft, designed for multiple programming languages including Python, JavaScript, C++, and more. It offers an integrated terminal, powerful extensions, and features such as IntelliSense (smart code suggestions), debugging tools, and Git integration, making it highly suitable for developers across platforms like Windows, macOS, and Linux. With its customizable interface, developers can enhance productivity through extensions and themes from its marketplace, adapting the editor to their specific workflows and languages.

3.NVIDIA Jetpack SDK

NVIDIA JetPack SDK is a powerful software development kit tailored for creating applications on NVIDIA Jetson platforms, which are designed for edge AI and robotics. It encompasses a comprehensive suite of tools, libraries, and APIs that leverage NVIDIA's GPU architecture to deliver high-performance computing capabilities, particularly in artificial intelligence, machine learning, and computer vision. JetPack includes essential components such as the CUDA Toolkit for parallel comput-

ing, cuDNN for optimizing deep neural networks, and TensorRT for high-performance inference, along with multimedia APIs and support for popular machine learning frameworks like TensorFlow and PyTorch. By providing developers with the resources needed to build and deploy sophisticated applications, JetPack SDK plays a crucial role in advancing technologies in robotics, autonomous machines, smart cities, and various industrial applications. .

4.3 Mechanical Design Details

The mechanical design of this conveyor belt setup involves a carefully constructed assembly of various components, including the roller, shaft, motor holding bracket, roller spacer, bearing holder, net holder, and nylon roller, all built to meet the load-bearing and operational requirements specified.

The roller is crafted from durable nylon, chosen for its corrosion resistance, lightweight properties, and smooth surface, which reduces friction with the conveyor belt. It has a diameter of approximately 6 mm and a length of 47 cm, ensuring that the belt remains stable during operation. Nylon caps are fitted at each end of the roller to keep it securely in place on the shaft, preventing lateral movement while providing smooth rotational motion. The shaft that supports this roller is made from either steel or aluminum, selected based on the balance between weight and strength requirements. Its diameter matches the inner dimensions of the bearing and the roller's mounting holes, ensuring compatibility and stability. The shaft is about 50 cm long, giving it a slight overhang at each end to allow secure mounting with nuts and washers. Threaded ends are machined onto the shaft to provide tight, adjustable connections within the frame. A robust motor holding bracket made from mild steel or aluminum is used to secure the motor to the conveyor frame. This bracket, typically about 5-10 cm wide and 10-15 cm long with a thickness of 5 mm, includes adjustable slots to facilitate precise alignment with the roller, ensuring effective power transmission. Reinforced and vibration-resistant, this bracket ensures the motor remains securely in place. Between the roller and other components, roller spacers are inserted, made from either plastic or rubber to minimize vibration and absorb shocks. These spacers, about 10 mm thick, serve to evenly space the roller and reduce friction, preventing direct contact with the motor or bearings and enhancing overall durability.

To support the shaft ends, bearing holders are mounted to the conveyor frame, housing pillow block bearings that allow for smooth rotational movement of the roller while

carrying the load from the conveyor belt. These bearing holders, made from aluminum or steel, are designed to withstand high radial loads and are equipped with grease fittings for easy maintenance. A net holder, fashioned from steel mesh or nylon netting, is fitted over the conveyor belt to provide a secure containment area for items as they move along the belt. This holder is adjustable and removable, allowing easy cleaning and maintenance. It is clipped or bolted securely to the conveyor frame, allowing the netting to sit slightly above the belt for effective containment without obstructing visibility.

The conveyor belt itself, made from a material such as rubber or PVC, is designed to support loads up to 2 kg. It has an anti-slip surface to prevent items from moving unintentionally during operation. Its width is slightly narrower than the roller (approximately 45 cm) to prevent overhang, and the belt tension can be adjusted via screws or bolts, ensuring it stays firm and aligned during use.

Finally, the nylon roller with a diameter of 6 mm and length of 47 cm serves as the driving mechanism for the belt, providing a smooth surface and minimal friction. It is fitted with bearing caps that allow easy mounting onto the shaft, ensuring consistent rotation with minimal resistance. This assembly ensures the conveyor belt operates efficiently and safely, with each component designed to facilitate easy maintenance and long-term durability. Together, these components work to create a conveyor system capable of reliably handling and transporting items, with all parts carefully aligned and secured to withstand the specified load requirements.

4.3.1 Conveyor belt

The mechanical design of a conveyor belt system consists of various components engineered to transport items efficiently across a defined path. Key elements include the drive roller, support rollers, motor, frame, belt, and tensioning system, each chosen to ensure durability, stability, and smooth operation. The conveyor belt is made of a

strong, flexible material that can carry items securely, with a width and surface suited to the weight and size of transported items.

The drive roller, connected to the motor, powers the belt's movement. This roller is often coupled with a shaft and mounted within a motor holding bracket to provide stability. Bearings are included within the roller assembly to minimize friction, ensuring efficient rotation and durability. To maintain tension and prevent slippage, a set of tension rollers or an adjustable roller spacer is positioned on the opposite side of the drive roller, allowing easy adjustments to keep the belt taut. Support rollers are placed underneath the belt to prevent sagging, ensuring the belt remains level while in motion.

The motor, mounted on a bracket, provides rotational power and is sized according to the weight and load-bearing requirements of the belt. The conveyor frame, typically constructed of aluminum or steel, houses the rollers and motor and offers structural support for the entire system. For systems with high load or continuous operation, reinforced frames and larger rollers with improved bearings are used to enhance longevity. The use of a PWM motor controller with speed regulation capabilities allows fine-tuned control over the conveyor speed, making the system adaptable to various operational needs.

To accommodate different applications, such as sorting or quality control, the conveyor may be equipped with sensors like IR or ultrasonic sensors to detect objects or measure distance, enabling automated responses. Additionally, end brackets are included to keep items from falling off the belt at transition points. This mechanical design ensures the conveyor belt system operates efficiently, handling loads up to a specified capacity, and provides the reliability necessary for industrial automation and material handling applications.

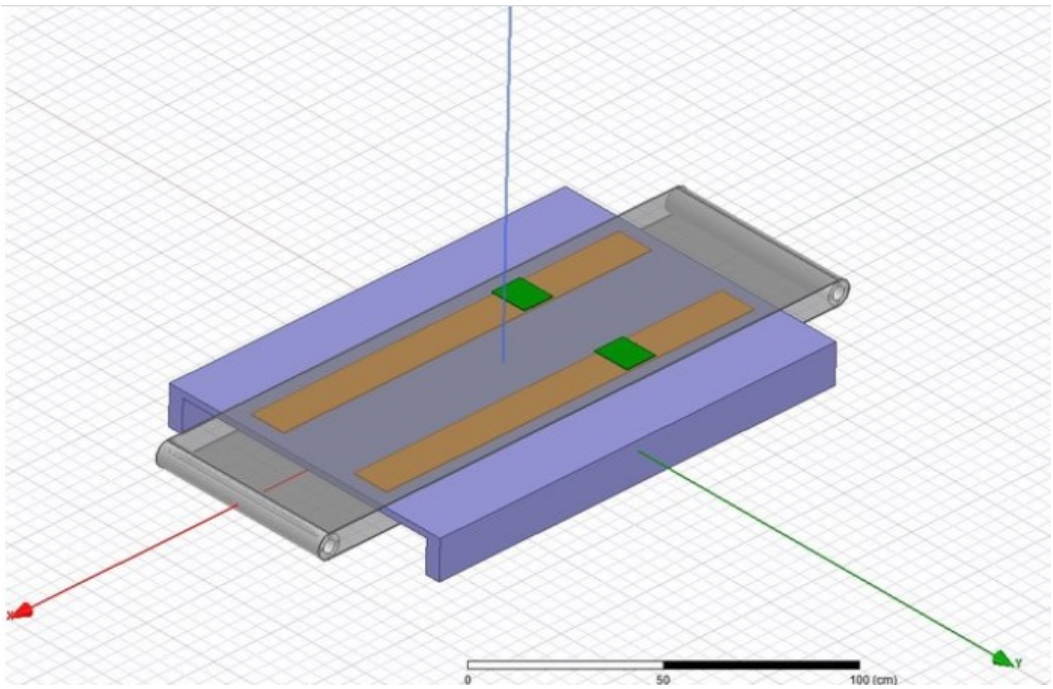

Figure 4.18: Conveyor belt

4.3.2 Motor holders bracket

The motor holder bracket in a conveyor belt system is a sturdy, precisely designed component used to secure the motor in place, ensuring reliable and vibration-free operation. Typically crafted from durable materials such as steel or aluminum, the bracket is engineered to bear the motor's weight and absorb the mechanical stresses generated during operation. It is custom-fitted for the motor type in use, with mounting holes that align with the motor's base and housing, allowing for easy installation and firm attachment.

The bracket is designed with slots or adjustable holes to enable fine-tuning of the motor's position. This adjustability is essential in conveyor systems, as it allows for optimal alignment of the drive shaft with the conveyor's drive roller, reducing strain on the motor and preventing belt slippage. The bracket's design also considers airflow around the motor, ensuring sufficient ventilation to prevent overheating, which is crucial for continuous or high-speed operations.

For added stability, the bracket is typically mounted on the conveyor frame using bolts or welding. In setups with heavy-duty motors, additional support brackets or reinforcement plates may be added to enhance stability and reduce vibration, minimizing wear on both the motor and the bracket. Some motor brackets also incorporate rubber padding or vibration-dampening materials, further reducing noise and mechanical stress, which contributes to the overall durability of the conveyor system. This bracket is a key component that provides a secure foundation for the motor, ensuring consistent power transmission to the conveyor belt with minimal maintenance.

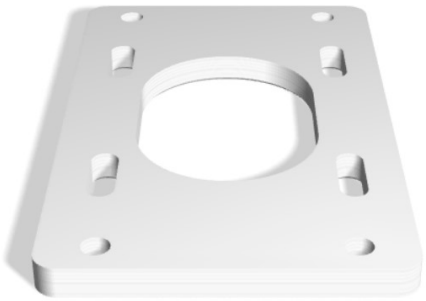

Figure 4.19: Motor holders bracket

4.3.3 Roller spacer

The roller spacer in a conveyor belt system serves as a critical component that maintains an optimal distance between the motor and the roller, ensuring proper alignment and smooth operation of the belt. Typically made from durable materials such as steel, aluminum, or high-density plastic, the spacer is precisely sized to fit the conveyor's shaft and align the motor drive shaft with the roller shaft. This alignment is crucial

for efficient power transfer from the motor to the roller, helping prevent undue wear on both components and minimizing vibrations during operation.

The spacer acts as a buffer, keeping the roller securely positioned on the shaft and preventing lateral movement, which could disrupt the alignment of the conveyor belt. In some systems, the roller spacer is also designed to reduce friction and absorb minor shocks, protecting the roller and motor from direct mechanical stress and enhancing the system's overall durability. Additionally, some roller spacers are fitted with grooves or flanges to ensure they stay securely in place, even under continuous or high-load conditions.

For easy assembly and disassembly, the roller spacer is often designed with set screws or snap-fit features, making it simple to install or remove when maintenance is required. Properly chosen and installed roller spacers contribute significantly to the longevity and reliable performance of the conveyor system, allowing for precise alignment and smooth rotation of the roller with minimal resistance or misalignment.

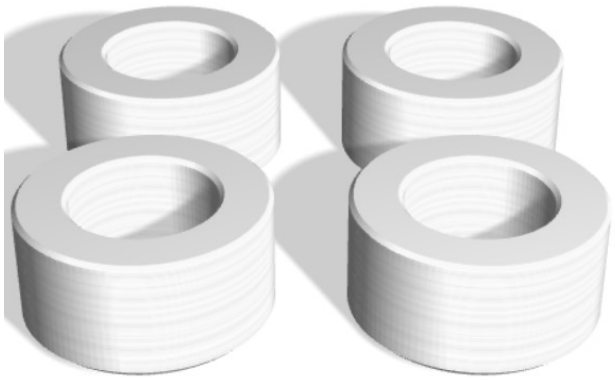

Figure 4.20: Roller spacer

4.3.4 Nut holders

Nut holders are integral components in mechanical systems that require secure fastening, providing stable housing for nuts to prevent rotation or loosening during operation. In conveyor belt systems, nut holders are used to attach various components—such as motor brackets, bearing holders, or roller supports—firmly to the conveyor frame or structure. These holders ensure that nuts stay in place, allowing bolts to be easily tightened or loosened as needed while maintaining a secure connection.

Nut holders are typically constructed from sturdy materials such as steel, aluminum, or reinforced plastic, which offers durability and resistance to wear in industrial environments. Designed for ease of assembly and maintenance, they often feature molded or machined grooves that align with the nut's shape, locking it into place to prevent slippage during vibration or heavy load-bearing. This locking feature is essential for maintaining the integrity of the conveyor system, particularly in applications with continuous or heavy-duty use.

In many cases, nut holders are designed with threaded inserts or self-locking mechanisms to further enhance their grip, reducing the risk of nuts loosening over time. Some nut holders are designed to accommodate multiple nuts or come with a modular configuration that allows easy adjustments for spacing and alignment. Their design aids in reducing assembly time and simplifying repairs or component replacements, ensuring that parts can be adjusted without detaching the entire setup.

Nut holders contribute significantly to the operational stability and safety of conveyor systems, allowing for secure attachments that can withstand mechanical stresses. By keeping nuts firmly in place, they help prevent alignment shifts and ensure the consistent performance of the conveyor belt, ultimately contributing to the reliability and efficiency of the entire system.

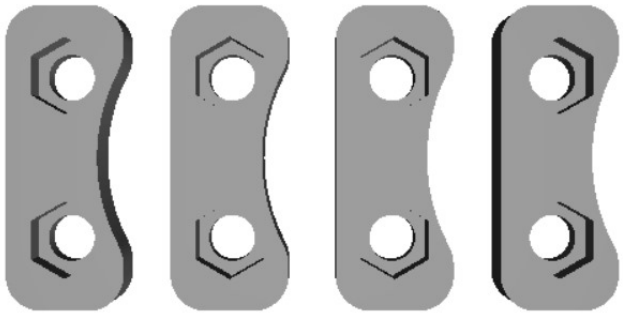

Figure 4.21: Nut holders

Chapter 5

RESULT

This section of the project report focuses specifically on the outcomes of the MobileNetV2 model used for banana quality classification. It presents a series of images that illustrate the model's performance in real-time scenarios, highlighting its ability to analyze and categorize bananas based on quality parameters. The results provide insights into how well the model distinguishes between different quality levels, offering a reliable and efficient approach for automated fruit quality assessment.

The MobileNetV2 model, designed for efficient performance on mobile and embedded systems, demonstrated commendable results in classifying banana quality. After extensive training on a diverse dataset containing thousands of images, the model successfully categorized bananas into predefined quality labels, such as "good," "bad," and "mixed." The classification process is based on key visual attributes, including texture variations, color differences, and the presence of defects such as bruises or over-ripeness. The presented images illustrate the model's capability to analyze these significant features, which are crucial for accurate quality assessment.

One of the key advantages of MobileNetV2 is its lightweight architecture, which enables fast inference while maintaining a high level of accuracy. Given the constraints of real-time processing in agricultural automation, the model's ability to efficiently classify bananas with minimal computational resources makes it well-suited for deployment on edge devices like the Jetson Nano. The low power consumption and optimized performance of MobileNetV2 ensure that banana classification can be performed continuously, even in resource-limited environments, without compromising accuracy.

Additionally, the model's performance was validated through multiple test cases,

including scenarios with varying lighting conditions, different angles of banana placement, and diverse background environments. The results indicate that MobileNetV2 maintains consistent classification accuracy across these variations, reinforcing its robustness in real-world applications. The integration of this model into an automated quality inspection system allows for significant reductions in manual labor while improving the efficiency and reliability of banana sorting processes.

The real-time classification results highlight the practical benefits of using MobileNetV2 in agricultural automation. The model contributes to enhanced productivity by ensuring that only high-quality bananas proceed to packaging while identifying and filtering out defective ones. This automated approach minimizes human intervention, reduces errors associated with manual inspection, and improves overall quality control in banana production.

With its optimized balance between classification accuracy and computational efficiency, MobileNetV2 presents a scalable and cost-effective solution for fruit quality monitoring. By leveraging deep learning, this system supports precision agriculture and industrial automation, ultimately leading to improved standards in banana quality assessment and supply chain management.

5.1 Output of MobileNet

The MobileNetV2 model excelled in classifying banana quality, successfully categorizing them into various labels such as "good," "bad," and "rotten." The model's lightweight design enables efficient processing, making it suitable for deployment on compact devices like the Jetson Nano. The results highlight the model's capability to analyze key features, such as texture and color, essential for accurate quality assessment. This effectiveness in quality monitoring demonstrates its potential to enhance productivity and reduce the need for manual inspection in agricultural settings.

Figure 5.1: Prediction: good (100.00%)

```
 Using device:  cpu
Model loaded successfully from
banana_mobilenet_best.pt
Class names:  ['bad', 'good',
'inter']
Image:  OIP(1).jpg
Prediction:  good (Confidence:
100.00%)
Class probabilities:
       bad:  0.00%
       good:  100.00%
       inter:  0.00%
```

Figure 5.2: Prediction: intermediate (82.26%)

```
 Using device:  cpu
Model loaded successfully from
banana_mobilenet_best.pt
Class names:  ['bad', 'good',
'inter']
Image:  OIP(1).jpg
Prediction:  intermediate
(Confidence:  82.26%)
Class probabilities:
       bad:  2.70%
       good:  15.04%
       inter:  82.26%
```

Figure 5.3: Prediction: bad (100.00%)

```
 Using device:  cpu
Model loaded successfully from
banana_mobilenet_best.pt
Class names:  ['bad', 'good',
'inter']
Image:  OIP(1).jpg
Prediction:  good (Confidence:
100.00%)
Class probabilities:
      bad:  100.00%
      good:  0.00%
      inter:  0.00%
```

5.1.1 Confusion Matrix

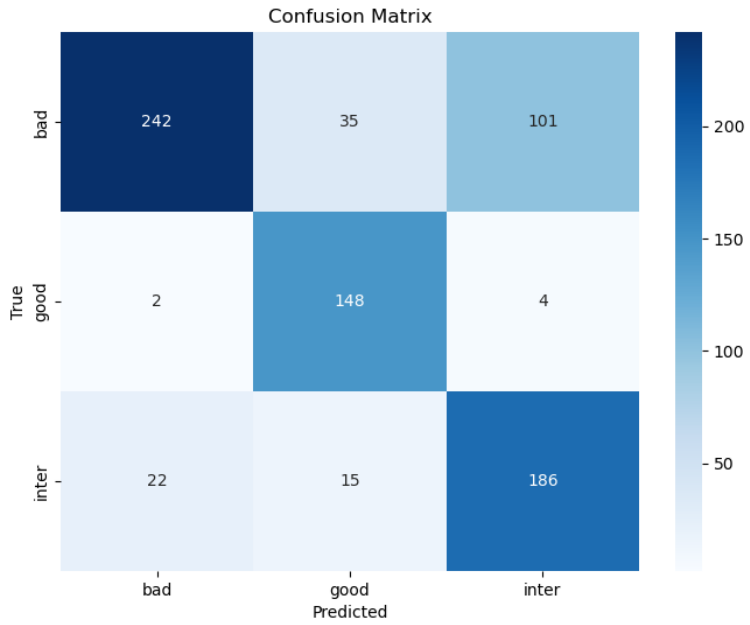

Figure 5.4: Confusion Matrix of MobileNetV2

The confusion matrix illustrates the performance of the MobileNetV2 model on the test data, providing details on true positives, false positives, true negatives, and false negatives. The confusion matrix obtained from the classification model highlights the model's ability to correctly classify different banana quality classes.

5.1.2 Training and Validation Accuracy Graph

The training and validation accuracy over the epochs are presented to illustrate the progression of the model's learning and performance. The MobileNetV2 model demonstrates steady learning, with a moderate increase in both training and validation accuracy over time. The model is tuned to prevent substantial overfitting, evident from the relatively parallel trends in accuracy between the training and validation datasets. The absence of extreme divergence indicates that the model has successfully learned meaningful features from the input data, ensuring reliable generalization across unseen samples.

Moreover, the training graph reveals the model's ability to adapt and refine its weights effectively, showcasing a validation accuracy that stabilizes around 0.65. Although this performance level is intermediate, it highlights the model's potential for further improvement through additional data augmentation or fine-tuning techniques. The convergence pattern suggests that with more extensive training or hyperparameter optimization, the model could achieve higher accuracy levels. Overall, the MobileNetV2 architecture provides a promising foundation for banana classification, balancing complexity and efficiency while maintaining acceptable predictive capabilities for real-world applications.

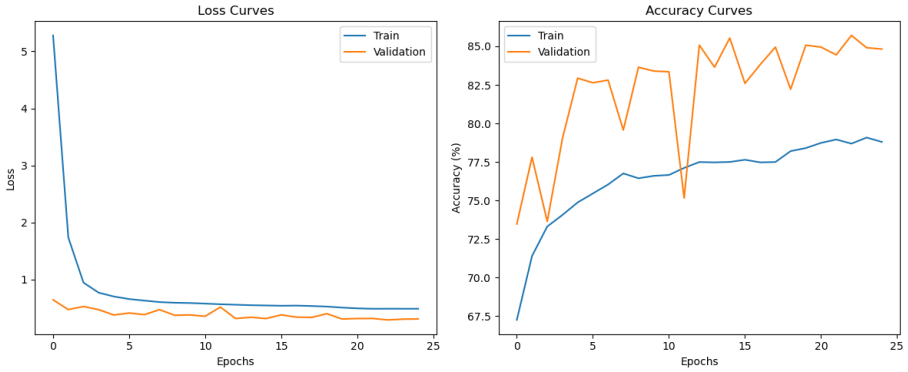

Figure 5.5: Training and Validation accuracy of MobileNetV2

5.2 Classification Metrics

In order to evaluate the performance of the MobileNetV2 model for banana quality classification, standard classification metrics such as **Precision, Recall, and F1-score** were used. These metrics provide insights into the effectiveness of the model in distinguishing between different quality classes.

Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It measures how many of the instances predicted as a certain class actually belong to that class. It is given by:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5.1}$$

where:

- TP (True Positives) are correctly predicted positive instances.
- FP (False Positives) are incorrectly predicted positive instances.

Recall

Recall (also known as Sensitivity or True Positive Rate) measures the ability of the model to correctly identify all relevant instances. It is defined as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5.2}$$

where:

- FN (False Negatives) are actual positive instances that were incorrectly classified as negative.

F1-score

The F1-score is the harmonic mean of Precision and Recall, providing a balanced measure of model performance when there is an uneven class distribution. It is given by:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.3}$$

A higher F1-score indicates better overall classification performance by balancing both Precision and Recall.

Interpretation

These metrics were computed for each class (Good, Intermediate, and Bad) in the banana quality classification task. A high Precision value means that the model produces fewer false positives, while a high Recall value indicates that fewer actual instances were missed. The F1-score provides a single measure of the model's effectiveness, making it useful for evaluating overall classification performance.

Good Quality Bananas

The model performed well in identifying good-quality bananas, achieving a high recall of 1.00, meaning almost all good bananas were correctly classified. The precision was 0.88, indicating that most of the predictions labeled as "Good" were indeed correct. The F1-score of 0.94 reflects a strong balance between precision and recall, confirming that the model effectively distinguishes high-quality bananas from other categories.

Intermediate Quality Bananas

The classification of intermediate-quality bananas showed some limitations. The precision was notably high at 0.98, meaning that when the model predicted a banana as "Intermediate," it was usually correct. However, the recall was relatively low at 0.50, suggesting that many actual intermediate bananas were misclassified as either "Good" or "Bad." This resulted in an F1-score of 0.66, indicating that the model struggles to identify intermediate-quality bananas effectively. Potential improvements could include increasing the number of training samples for this class or refining the feature extraction process.

Bad Quality Bananas

The model demonstrated strong recall (0.96) for bad-quality bananas, meaning it correctly detected most of the bananas that were actually bad. The precision was 0.75,

implying that some bananas classified as "Bad" may belong to other categories. With an F1-score of 0.85, the model performed reasonably well in detecting bad-quality bananas, but further fine-tuning may be needed to reduce false positives.

Class	Precision	Recall	F1-Score	Support
Good	0.90	1.00	0.94	154
Intermediate	0.97	0.50	0.66	223
Bad	0.76	0.95	0.85	378
Accuracy		0.83		755
Macro Avg	0.88	0.81	0.82	755
Weighted Avg	0.85	0.83	0.81	755

Table 5.1: Classification Report for Banana Quality Detection

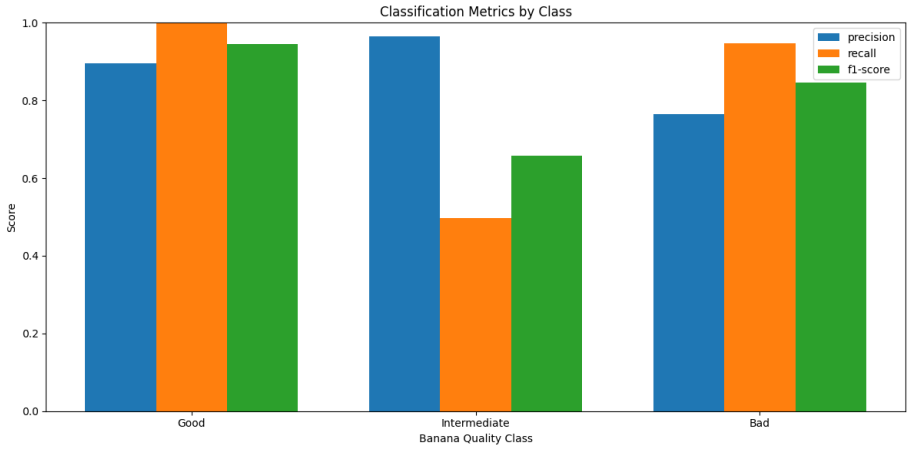

Figure 5.6: Classification Metrics by class

5.3 Conveyor Belt Systems

Conveyor belt systems are widely used in industrial automation and material handling processes. They consist of a continuous belt that moves items from one location to another, driven by motors and guided by rollers. These systems are highly efficient and customizable, making them suitable for various applications, including sorting, packaging, and quality control. In modern applications, conveyor belts are often integrated with vision systems and machine learning models to enable automated decision-making

and quality assurance.

5.3.1 Primary Conveyer Belt

The conveyor belt system used in this project incorporates an illumination box to ensure consistent lighting conditions during image capture. The illumination box is strategically placed above the belt and is equipped with LED strips to provide uniform lighting, minimizing shadows and glare. This setup enhances the quality of images captured by the camera positioned inside the box, allowing for accurate feature extraction and analysis.

Figure 5.7: Conveyor Belt with Illumination Box

5.3.2 Secondary Conveyer Belt

To facilitate the sorting of objects, the conveyor belt system is designed to rotate in both clockwise and anti-clockwise directions. The direction of rotation is dynamically controlled based on the results of the machine learning model. If the classification result indicates that the object meets the desired quality standard, the belt moves

Figure 5.8: Conveyor Belt with Illumination Box

forward (clockwise) to direct the item towards the acceptance bin. Conversely, if the object does not meet the standard, the belt reverses (anti-clockwise) to direct it towards the rejection bin.

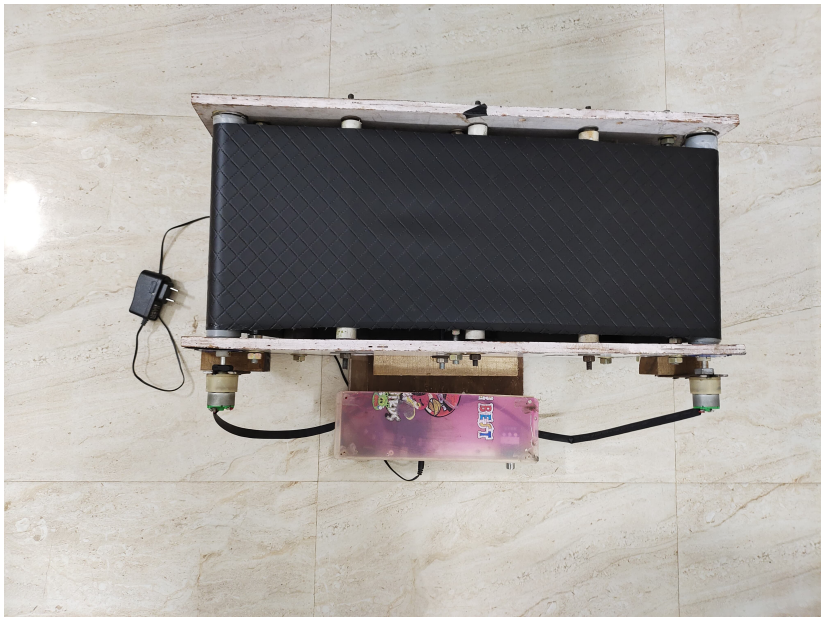

Figure 5.9: Conveyor Belt for Sorting

Chapter 6

CONCLUSION

The banana classification project leverages advanced technologies and methodologies to create a system capable of accurately assessing the quality of bananas based on visual characteristics. The project focuses on quality detection using a CNN trained on a diverse dataset of banana images, achieving commendable accuracy levels across multiple quality categories, including export quality, good, bad, and rotten. The development and deployment of the banana quality detection model on the Jetson Nano platform showcase promising results in real-time classification. The successful integration of the model with the Jetson Nano hardware enables efficient and rapid inference directly on edge devices, facilitating real-time quality assessment applications without the need for constant internet connectivity or reliance on cloud-based processing. This deployment offers advantages such as reduced latency, enhanced privacy, and increased autonomy in various use cases, including automated sorting systems, agricultural monitoring, and supply chain optimization. However, challenges were encountered in optimizing the conveyor belt system for seamless integration with the model due to technical constraints. While the current model performance is notable, ongoing optimization efforts, including fine-tuning the model architecture, hyperparameter tuning, and continuous data collection and augmentation, are essential to further improve accuracy and robustness. Additionally, exploring advanced techniques such as transfer learning and model compression tailored for edge deployment could enhance the model's efficiency and resource utilization on constrained hardware platforms like the Jetson Nano. The analysis of quality classifications over time can be visualized through bar plots, each representing the frequency of classified quality levels. Although further refinement is necessary to accurately assess the quality of the bananas, this

visualization provides insight into the potential of our system to monitor quality fluctuations effectively. Moving forward, additional enhancements and optimizations can be made to improve the system's robustness and effectiveness in delivering accurate quality assessments to users.

Despite achieving significant milestones, the banana quality detection system presents multiple avenues for future enhancements. The system can be expanded to include more refined quality categories, such as ripeness stages, pest infestation detection, or bruising severity, allowing for a more granular classification of banana quality. Integration with IoT-enabled smart farming systems can enable real-time monitoring and automated decision-making, improving agricultural efficiency. Additionally, improving the conveyor system using AI-driven control mechanisms can enhance sorting precision and efficiency. Optimizing the model further through techniques such as pruning, quantization, and TensorRT acceleration can significantly boost inference speed and reduce power consumption, making the system more suitable for edge AI applications. A mobile application or cloud integration could allow users to monitor quality assessments remotely and analyze trends over time, increasing accessibility and usability. Expanding the dataset by collecting images from various sources under different lighting conditions and environments can improve the model's generalizability, ensuring its effectiveness across diverse scenarios. Implementing transfer learning with larger pre-trained models can further enhance classification performance across different banana varieties. Furthermore, collaborating with agricultural experts can provide valuable insights to fine-tune the system based on real-world farming and supply chain requirements. These future developments will enhance the reliability, efficiency, and commercial viability of the banana quality detection system, making it an indispensable tool for modern agricultural and food distribution sectors.

Chapter 7

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Chapter 8

APPENDIX

8.1 Project Plan

- **Week 1** - 09/12/24 - 15/12/24
  - Work on Mechanical Design of the Conveyor Belt System
  - Develop Software Programming for camera module integration
  - Test and integrate ultrasonic sensor for object detection with Jetson Nano
- **Week 2** - 16/12/24 - 22/12/24
  - Dataset Collection & Preprocessing (Capturing banana images under different lighting conditions)
  - Continue working on Mechanical Design modifications
  - Test and integrate Conveyor Belt Motor with Jetson Nano
- **Week 3** - 30/12/24 - 05/01/25
  - Begin 3D Printing of mechanical components (if required)
  - Test and integrate Stepper Motor for Conveyor Belt Control
- **Week 4** - 06/01/25 - 12/01/25
  - Train MobileNetV2 for banana quality classification (Good, Bad, Intermediate)
  - Optimize Jetson Nano hardware setup for real-time image processing

- **Week 5** - 13/01/25 - 19/01/25
  - Sensor Integration & Testing (Camera, Motor, Ultrasonic Sensor)
  - Model Calibration & Modification based on test results
  - Begin Hardware Implementation of the complete system
- **Week 6** - 20/01/25 - 26/01/25
  - Finalize Hardware and Mechanical Model Integration
  - Optimize Data Processing Pipeline for real-time classification
  - Ensure Jetson Nano performance tuning for smooth operation
- **Week 7,8** - 27/01/25 - 09/02/25
  - Overall Integration of the System
- **Week 9,10** - 10/02/25 - 23/02/25
  - Final Testing
  - Debugging

8.2 GANTT CHART

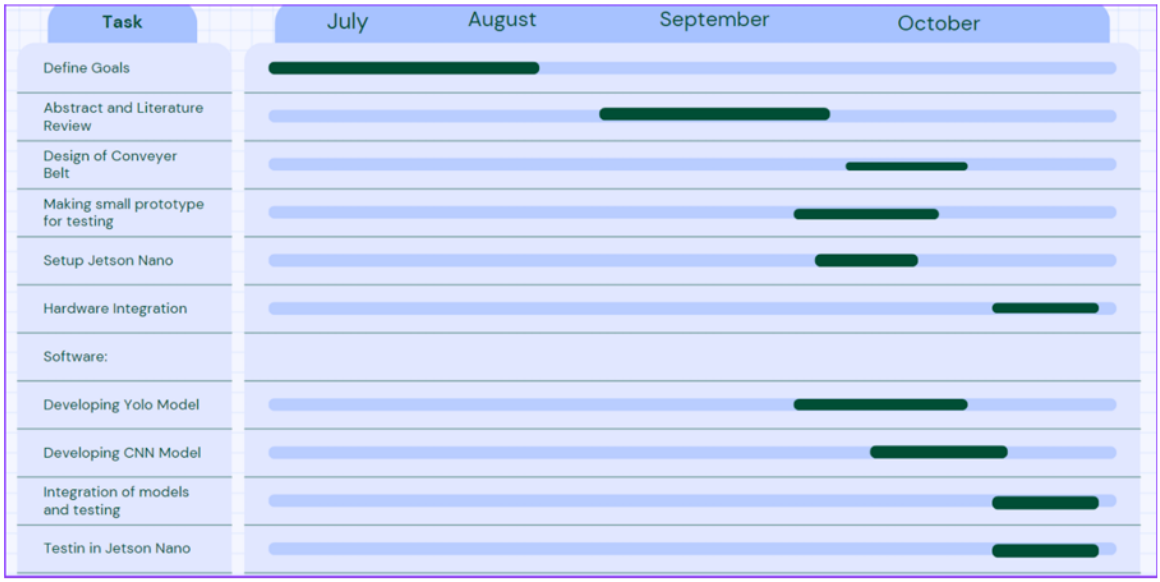

Figure 8.1: S7 Gantt Chart

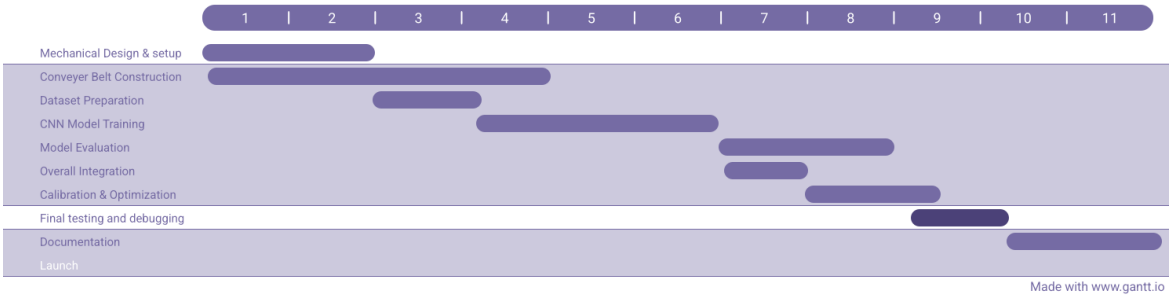

Figure 8.2: S8 Gantt Chart

8.3 PERT CHART

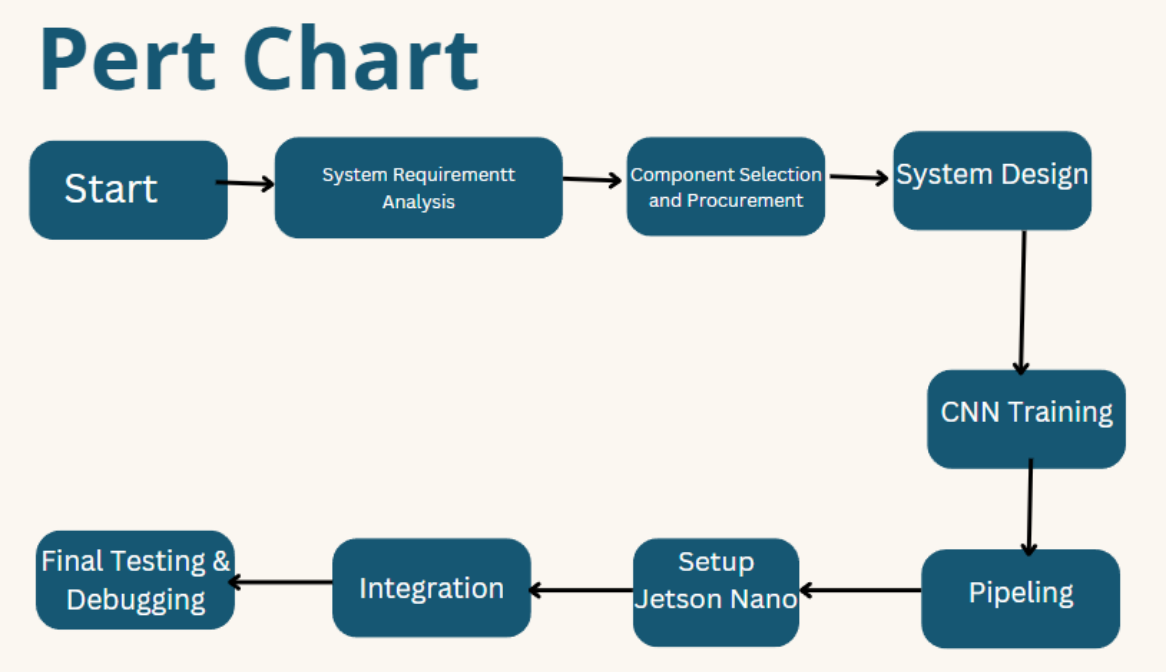

Figure 8.3: Pert Chart

8.4 WORK SCHEDULE

Sl. No.	Task	Member(s)
1	Research, Planning, and Mechanical Design	Muhammed Hadhi V M and Rohith
2	Making small prototype for testing	Muhammed Hadhi and Adithyan
3	Assembly and Integration	Muhammed Hadhi and Adithyan
4	Testing Conveyor Belt	Muhammed Hadhi V M
5	Setting up the Jetson Environment	Rohith M S and Ruben
6	Setting up the sorting mechanism	Muhammed Hadhi V M
7	Optimizing the ML model into TensorRT format	Rohith M S and Ruben
8	Testing and Validation	Muhammed Hadhi V M
9	Develop CNN Model	Adithyan Manoj
10	Integration of models and testing	Ruben and Rohith
11	Testing in Jetson Nano	Ruben and Rohith

Table 8.1: Task Distribution and Members Involved

8.5 DETAILED BUDGET

Component	**Quantity**	**Price**
Jetson Nano	1	15000
DC Motor	5	1000
LED Strip	1	165
USB Camera	1	1500
Bearing	20	1200
OLED Display	1	200
Motor Driver	2	200
Nylon Roll	1	300
Ultrasonic Sensor	3	360
PWM Modulator	2	400
Arduino Uno	2	1000
Accessories (screw, bolt, thread)	40	1500
Total		21325

Table 8.2: Component List with Quantity and Price