AUTOMATED SILKWORM DISEASE IDENTIFICATION AND ISOLATION SYSTEM USING ROBOTIC ARM

A PROJECT REPORT

Project Work II Phase II

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
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BONAFIDE CERTIFICATE

This is to certify that the project work II phase II report entitled **AUTOMATED SILKWORM DISEASE IDENTIFICATION AND ISOLATION SYSTEM USING ROBOTIC ARM** is the bonafide record of project work done by **JEGAN M (21ECR089), JEGAN P (21ECR090), MEIPRASAANTH V (21ECR116)** in partial fulfilment of the requirements for the award of the Degree of Bachelor of Engineering in Electronics and Communication of Anna University, Chennai during the year 2024-2025.

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DECLARATION

We affirm that the project work II phase II report titled **AUTOMATED SILKWORM DISEASE IDENTIFICATION AND ISOLATION SYSTEM USING ROBOTIC ARM** being submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering is the original work carried out by us. It has not formed the part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Sericulture, the process of cultivating silkworms for silk production, is a labour-intensive industry vulnerable to diseases such as Pebrine (protozoan), Flacherie (bacterial), Grasserie (viral), and Muscardine (fungal). These infections can spread rapidly within dense silkworm populations, leading to economic losses and reduced silk quality. Traditional disease detection methods rely on manual inspection, which is time-consuming, error-prone, and dependent on human expertise. Delayed identification further exacerbates disease spread, impacting overall silk production. To address these challenges, this project proposes an Automated Silkworm Disease Identification and Isolation System that integrates AI-driven image processing and robotic automation for efficient disease management. The system utilizes a YOLOv8-based deep learning model with an overall mAP50 of 95.4% (91% for healthy silkworms and 99% for diseased ones), ensuring high detection accuracy. The classification model achieves a precision of 85.7% and recall of 96.6%, enabling reliable identification of infected silkworms. Upon detection, a robotic arm with a servo-operated gripper and stepper motor-driven linear movement isolates diseased silkworms, preventing the spread of infection. The arm is mounted upside down on an aluminum rod with bearings for stable operation. This automation reduces human intervention, minimizes errors, and enables early disease detection, significantly enhancing productivity in sericulture farms. The proposed system contributes to sustainable silk farming by improving disease control, reducing labour costs, and increasing silk yield through AI-powered precision farming.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
DOF	Degrees of Freedom
FPS	Frames Per Second
FOV	Field of View
HSV	Hue-Saturation-Value
IMU	Inertial Measurement Unit
IoT	Internet of Things
IoU	Intersection over Union
GND	Ground
GPIO	General-Purpose Input/Output
mAP	Mean Average Precision
MG995	Metal Gear Servo Motor
NEMA	National Electrical Manufactures Association
PCB	Printed Circuit Board
PWM	Pulse Width Modulation
RNN	Recurrent Neural Network
ROS	Robot Operating System
RPM	Revolutions Per Minute
SMPS	Switched Mode Power Supply
UART	Universal Asynchronous Receiver-Transmitter
VCC	Voltage Common Collector
YOLO	You Only Look Once

CHAPTER 1

INTRODUCTION

Silk production is a highly intricate and delicate process, relying on the healthy growth of silkworms under carefully controlled conditions. Maintaining optimal environmental factors such as temperature, humidity, and hygiene is crucial, but disease outbreaks remain one of the most significant challenges in sericulture. Diseases like Pebrine, Flacherie, Grasserie, and Muscardine can rapidly spread in silkworm populations, leading to substantial economic losses and decreased silk quality. Traditionally, manual inspection has been the primary method for disease identification, requiring skilled laborers to visually examine silkworms and remove the infected ones. However, this approach is labor-intensive, time-consuming, and prone to human error, making it inefficient for large-scale silk farming.

However, the challenge of early disease detection and containment remained largely unresolved. To address this, the present project enhances the SmartGrid system by integrating an AI-based silkworm disease identification and isolation system using deep learning and robotic automation. The system employs YOLOv8-based image processing to analyze real-time images of silkworms, effectively classifying them as healthy or diseased. Once infected silkworms are detected, a robotic arm autonomously picks and isolates them, preventing further disease transmission and ensuring the protection of healthy silkworms. This automated approach significantly reduces human intervention while improving the accuracy and efficiency of disease management.

To achieve seamless real-time execution, the system is built using a combination of Raspberry Pi, Arduino, a Pi Camera, NEMA 17 stepper motors, and high-precision servo motors. The integration of AI-based image processing, robotics, and real-time decision-making ensures a highly efficient and scalable disease management solution for the sericulture industry. The implementation of this advanced disease management system is expected to enhance productivity, minimize losses, and improve silk quality by ensuring early disease detection and rapid response. With the growing demand for sustainable and technology-driven agriculture, this project represents a significant step toward modernizing sericulture through automation and artificial intelligence.

1.1 OBJECTIVE

The project aims to focuses on automating the identification and isolation of diseased silkworms using AI-based image processing and a robotic arm for pick-and-place operations, ensuring timely removal of affected silkworms to prevent disease spread and enhance productivity.

1.2 SCOPE

The scope of this project encompasses to automate silkworm disease identification and isolation using AI-based image processing and robotic automation to improve sericulture efficiency. Traditional manual inspection is time-consuming and error-prone, making large-scale disease management challenging. The proposed system leverages YOLOv8 deep learning for accurate disease detection and a robotic arm for swift isolation, preventing disease spread and minimizing losses. Designed for commercial sericulture farms, research institutions, and automated silk production units, the system is scalable and adaptable for both small and large setups. It integrates seamlessly with smart sericulture frameworks like the Automated Sericulture Smart Grid using Raspberry Pi, Arduino, and motorized controls. By reducing manual labour, improving detection accuracy, and enabling real-time intervention, this project enhances productivity, reduces economic losses, and modernizes silk farming. The integration of AI-driven automation advances precision agriculture, ensuring a more efficient and sustainable sericulture industry.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE REVIEW

The automation of sericulture has been explored in various studies, with a focus on integrating IoT, AI, and robotic systems to enhance efficiency, disease control, and productivity. Several researchers have worked on Arduino-based automated environmental control systems for silkworm rearing. These systems regulate temperature, humidity, and light conditions to optimize silkworm growth and cocoon production. However, they lack an advanced disease detection and intervention mechanism, necessitating manual monitoring and response [1]. Studies on IoT-enabled smart sericulture frameworks have demonstrated the potential for automating feeding, environmental monitoring, and growth analysis. These systems leverage real-time data acquisition from sensors to ensure stable rearing conditions but do not incorporate AI-powered disease classification or robotic removal mechanisms, leaving disease management incomplete [2].

The development of intelligent control systems using IoT has allowed researchers to track silkworm feeding cycles, temperature, humidity, and CO_2 levels in real-time. Such systems improve larval health and cocoon yield but still rely on human intervention for detecting and isolating diseased silkworms, making them less efficient in preventing disease outbreaks [3]. Some researchers have explored fuzzy logic-based IoT systems for maintaining environmental stability, reducing mortality rates, and improving silk yield. These systems use smart sensors to maintain optimal conditions but do not integrate deep learning-based disease detection mechanisms, making early disease identification difficult [4]. IoT-driven real-time monitoring has been widely implemented in smart sericulture systems, improving disease tracking, environmental control, and feeding automation. However, most existing solutions lack robotic automation for the isolation of diseased larvae, limiting their ability to prevent disease spread [5]. Precision temperature regulation, such as airborne liquid cooling and controlled ventilation, has been explored to improve cocoon quality. These techniques ensure optimal rearing conditions, but their effectiveness in disease prevention is limited since they do not integrate disease detection mechanisms [6]. Machine learning and deep learning models have been successfully used in sericulture for cocoon grading and disease monitoring. Researchers have employed convolutional neural networks (CNNs) and YOLO-based models for disease classification, achieving high accuracy in detecting abnormalities in silkworm larvae. However, these models have not been combined with robotic isolation mechanisms, which are necessary for full automation in disease prevention [7]. Some studies have explored embedded vision-based techniques to automate silkworm monitoring. These systems use computer vision to track silkworm health over time, but they still require manual intervention for diseased silkworm removal [8].

Edge computing has been applied to sericulture, enabling real-time AI inference for disease detection and farm management. This reduces latency and improves system efficiency. However, even with real-time processing, these solutions lack the physical intervention of robotic systems for isolating infected silkworms [9]. Digital twin technology has also been explored for simulating sericulture environments and predicting disease outbreaks using AI-driven predictive models. While these simulations improve farm management strategies, they do not provide real-time solutions for disease removal, which remains a challenge [10]. The use of robotic arms in agriculture has shown potential for automating delicate tasks such as fruit picking and pest control. Researchers have proposed similar approaches for handling silkworms, using robotic arms to pick and sort larvae based on health status. However, practical implementations in silkworm disease isolation remain limited due to the complexity of integrating AI-based classification with robotic intervention [11]. Airflow-based robotic systems have been explored for handling delicate biological materials, suggesting a non-contact approach for silkworm isolation. However, these systems require further adaptation for disease management in sericulture [12].

Swarm robotics has been investigated for agricultural applications, demonstrating the feasibility of multi-robot coordination for large-scale farm automation. While this technology has been successfully applied to crop monitoring, its application in silkworm disease detection and removal remains unexplored [13]. Robotic rearing systems equipped with actuators and sensors have been developed to optimize environmental control. These systems maintain stable rearing conditions, but they lack an AI-integrated disease detection and isolation system, making disease management inefficient [14]. Researchers have developed AI-based models with over 95% classification accuracy for detecting diseasedsilkworms. Convolutional neural networks (CNNs) and transfer learning approaches, such as YOLOv8 and EfficientNet, have been tested for disease classification, significantly improving detection capabilities. However, without an automated robotic removal system, these models remain ineffective in preventing the spread of infections [15]. Some studies have explored multi-modal sensor fusion techniques to integrate various environmental data sources, such as temperature, humidity, and silkworm activity levels. These approaches enhance farm automation, but the lack of AI-powered disease intervention limits their application for disease control [16]. The use of near-infrared spectroscopy (NIRS) combined with chemometric analysis has been applied to high-speed sex identification of silkworm pupae. Similar non-invasive techniques could be adapted for disease detection in larvae, but this application remains largely unexplored [17]. AI-powered disease classification has been extended to dead cocoon analysis, improving silk quality assessment. However, early-stage disease detection in live silkworms has not yet been fully automated using these methods [18].

Some studies have proposed the use of predictive models based on environmental data analytics to estimate mulberry crop yields. These models help optimize silkworm feeding cycles, but they do not account for real-time disease monitoring, which is critical for sustainable sericulture [19]. IoT-enabled automated feeding systems have been developed to enhance efficiency and reduce manual labor. These systems optimize the nutritional intake of silkworms, but they lack integrated AI-based disease tracking, requiring manual inspections [20]. 6LoWPAN (IPv6 over Low-Power Wireless Personal Area Networks) technology has been utilized in smart sericulture systems to improve communication between sensors and cloud-based monitoring platforms. While these solutions enhance real-time data collection, they do not address disease isolation challenges, requiring additional AI-robotic integration for full automation [21]. Despite significant advancements in sericulture automation, a fully integrated AI and robotic-based disease detection and isolation system remains an open challenge. Current research has successfully implemented AI-driven classification models for disease detection, achieving high accuracyrates. However, the absence of automated robotic intervention limits their real-world applicability. Future research should focus on developing a seamless integration of deep learning-based classification models with robotic arms for real-time silkworm disease identification and isolation [22]. Additionally, advancements in non-invasive disease detection techniques, such as spectroscopy and hyperspectral imaging, could further improve early-stage identification of infected silkworms. Combining these methods with AI-driven decision-making and robotic automation could lead to a more efficient and sustainable sericulture industry [23]. A recent study explored the integration of a YOLOv8-based disease detection model with a Raspberry Pi-powered image processing unit. The research demonstrated the feasibility of real-time silkworm classification, but the robotic intervention for diseased silkworm isolation remained underdeveloped, necessitating further improvements in automated control mechanisms [24]. A novel approach has been proposed, integrating AI-powered disease detection with a robotic arm for automated silkworm isolation. This research marks a significant step toward fully automated sericulture disease management, though challenges remain in optimizing motion control and minimizing false positive detections [25].

2.2 SUMMARY FROM LITERATURE

- Automation in sericulture has been explored using Arduino and IoT-based systems to monitor temperature and humidity, ensuring optimal silkworm rearing conditions. However, these systems lack AI-driven disease detection and removal mechanisms.
- AI-based image processing is emerging as a key tool for silkworm health monitoring, with deep learning models such as CNNs and YOLO being used for classification. However, most studies focus on cocoon quality assessment rather than early-stage disease detection.
- IoT-enabled sericulture systems allow real-time monitoring of environmental factors, but current implementations do not integrate robotic automation for disease isolation, necessitating manual intervention.
- Robotic solutions in agriculture and sericulture have been proposed for automating feeding and waste management, yet research on robotic arms for diseased silkworm removal remains limited.
- Studies on AI-driven classification models demonstrate the potential of deep learning in disease identification but require further optimization for real-time processing in large-scale sericulture farms.
- Existing research lacks a fully integrated system that combines AI-based disease identification with an automated robotic arm for disease isolation, highlighting the need for an end-to-end solution in modern sericulture.

CHAPTER 3
METHODOLOGY

3.1 EXISTING METHOD

1. **Disease Identification:** In traditional sericulture, identifying diseased silkworms affected by Flacherie, Pebrine, Grasserie, and Muscardine is carried out through manual visual inspection by trained workers. Farmers rely on visible symptoms such as discoloration, sluggish movement, changes in body texture, and abnormalities in excretion to determine if a silkworm is infected. This method is highly dependent on human expertise and requires close and continuous monitoring throughout the rearing period. Since some diseases have latent periods before visible symptoms appear, early detection becomes difficult, leading to delayed intervention. Additionally, different diseases exhibit similar external symptoms, making it challenging to differentiate between infections.

   a. **Pebrine (Protozoan Disease)**

Figure 3.1 Pebrine

Figure 3.1 represents the Pebrine, a protozoan disease, its cause, mode of transmission, symptoms, stage affected, favourable condition where mentioned below,

- Cause: Nosema bombycis (a microsporidian protozoan)
- Mode of Transmission: Transmitted vertically (from infected moths to eggs) and horizontally (through contaminated food and excreta).

- Symptoms: Black speckled spots on the body, Poor appetite and sluggish movement, Uneven growth rate with some larvae appearing smaller than other.
- Stage Affected: Can affect all stages—egg, larva, pupa, and moth.
- Favorable Conditions: Spread is rapid under poor sanitation and unhygienic conditions in the rearing trays.

b. Flacherie (Bacterial Disease)

Figure 3.2 Flacherie

Figure 3.2 represents the Flacherie, a bacterial disease, its cause, mode of transmission, symptoms, stage affected, favourable condition where mentioned below,

- Cause: Bacteria such as *Streptococcus*, *Staphylococcus*, *Bacillus*, and *Serratia*.
- Mode of Transmission: Caused by ingestion of contaminated mulberry leaves, poor hygiene, or exposure to sudden temperature fluctuations.
- Symptoms: Larvae appear weak, sluggish, and soft-bodied, Vomiting of a yellowish-brown fluid, Silkworms lose appetite and fail to spin cocoons, Body becomes flaccid and discolored.
- Stage Affected: Mainly affects third to fifth instar larvae.
- Favorable Conditions: High humidity, poor ventilation, contaminated food, and sudden climatic changes increase bacterial infection risks.

c. Grasserie (Viral Disease)

Figure 3.3 Grasserie

Figure 3.1 represents the Grasserie, a viral disease, its cause, mode of transmission, symptoms, stage affected, favourable condition where mentioned below,

- Cause: Bombyx mori Nuclear Polyhedrosis Virus (BmNPV)
- Mode of Transmission: Spread through infected silkworm feces, contaminated food, and rearing tools.
- Symptoms: Silkworms become swollen, translucent, and fragile, Shiny skin with an enlarged body due to fluid accumulation, Excessive molting and delayed cocoon formation, Body bursts open upon touch, releasing milky white fluid containing viral polyhedral.
- Stage Affected: Affects mainly fourth and fifth instar larvae.
- Favorable Conditions: Warm and humid climates favor virus multiplication.

d. Muscardine (Fungal Disease)

Figure 3.4 Muscardine

Figure 3.4 represents the Muscardine, a fungal disease, its cause, mode of transmission, symptoms, stage affected, favourable condition where mentioned below,

- Cause: Beauveria bassiana (White Muscardine Fungus) and Metarhizium anisopliae (Green Muscardine Fungus).
- Mode of Transmission: Spread through spores in the air, high humidity, and poor ventilation in rearing trays.
- Symptoms: Silkworms become inactive, stiff, and hard,Fungal spores develop on the body, appearing white, green, or yellow depending on the fungal species, Mummified appearance before death.
- Stage Affected: Mostly affects late-stage larvae and pupae.
- Favorable Conditions: High humidity, low temperature, and poor ventilation favor fungal growth.

Challenges:

- Labor-intensive and requires skilled workers for accurate identification.
- Prone to human error, as minor infections may go unnoticed.
- Difficult to distinguish between different diseases due to overlapping symptoms.
- Early-stage infections are often missed, increasing disease spread among healthy silkworms.
- Not scalable for large sericulture farms, as manual monitoring is time consuming and impractical.

2. **Removal of Diseased Silkworms:** Once diseased silkworms are identified, they must be manually removed from the batch to prevent further contamination. Workers must physically pick up infected silkworms using tweezers or gloved hands and transfer them to a separate disposal area. However, this process is time-consuming and requires continuous effort, especially in large-scale sericulture farms where thousands of silkworms are reared simultaneously. The manual isolation of diseased silkworms is slow, and by the time removal is completed, the disease may have already spread to healthy silkworms.

Additionally, errors in identification can lead to healthy silkworms being mistakenly removed or infected ones being overlooked, resulting in further losses. Challenges:

- Extremely slow and inefficient, as each infected silkworm must be removed individually.
- High labour costs, as skilled workers are required to monitor and separate diseased silkworms.
- Delay in removal increases the chances of disease transmission within the batch.
- Large-scale farms struggle to manage manual disease isolation, leading to significant silk yield losses.
- Difficult to track disease progression, as manual methods do not provide data-driven insights.

3.2 PROPOSED METHOD

The proposed method integrates AI-based image processing and robotic automation to enhance silkworm disease identification and isolation. By implementing real-time deep learning classification and robotic intervention, this system ensures early detection, rapid removal of infected silkworms, and improved productivity in sericulture farms.

1. **Automated Disease Identification:** The system automates the process of detecting diseased silkworms using advanced image processing and AI-based classification, eliminating the need for manual inspection.
   - YOLOv8 Deep Learning Model: A pre-trained YOLOv8 model is used for real-time classification of silkworms as healthy or diseased based on symptoms of Flacherie, Pebrine, Grasserie, and Muscardine. The model is trained using Roboflow and deployed on Google Colab for high accuracy.
   - Pi Camera Integration: A Pi Camera continuously captures images of silkworms in the rearing trays. These images are processed by the YOLOv8 model, allowing early detection of diseases even before symptoms become visible.

- Real-Time Processing: The detection system runs continuously, ensuring instant identification of infected silkworms and reducing the spread of diseases.

Challenges Addressed:

- Eliminates manual labour dependency for disease identification
- Ensures faster and more accurate classification of diseased silkworms.
- Early detection minimizes disease outbreaks, reducing losses.
- Reduces human error in disease identification, improving efficiency.
- Can be scaled for large sericulture farms, enhancing disease monitoring.

2. **Automated Robotic Arm for Diseased Silkworm Removal:** The system includes a robotic arm to isolate diseased silkworms identified by the AI model, ensuring quick and effective removal.

- Pick-and-Place Mechanism: The robotic arm is equipped with a gripper and servo motors, which enable precise removal of infected silkworms without disturbing the healthy ones.
- X-Y-Z Coordinate Mapping: The arm operates using X-Y-Z coordinate mapping, ensuring precise positioning for picking up diseased silkworms detected by the AI model.
- Safe Isolation: Once picked up, infected silkworms are transferred to a containment area, preventing further contamination and minimizing disease spread.

Challenges Addressed:

- Faster and more efficient than manual silkworm removal.
- Reduces the spread of infection by ensuring immediate isolation.
- Minimizes labor costs, decreasing manual handling requirements.
- Improves accuracy, reducing errors in disease isolation.
- Suitable for large-scale farms, allowing seamless automation.

3.3 WORK FLOW

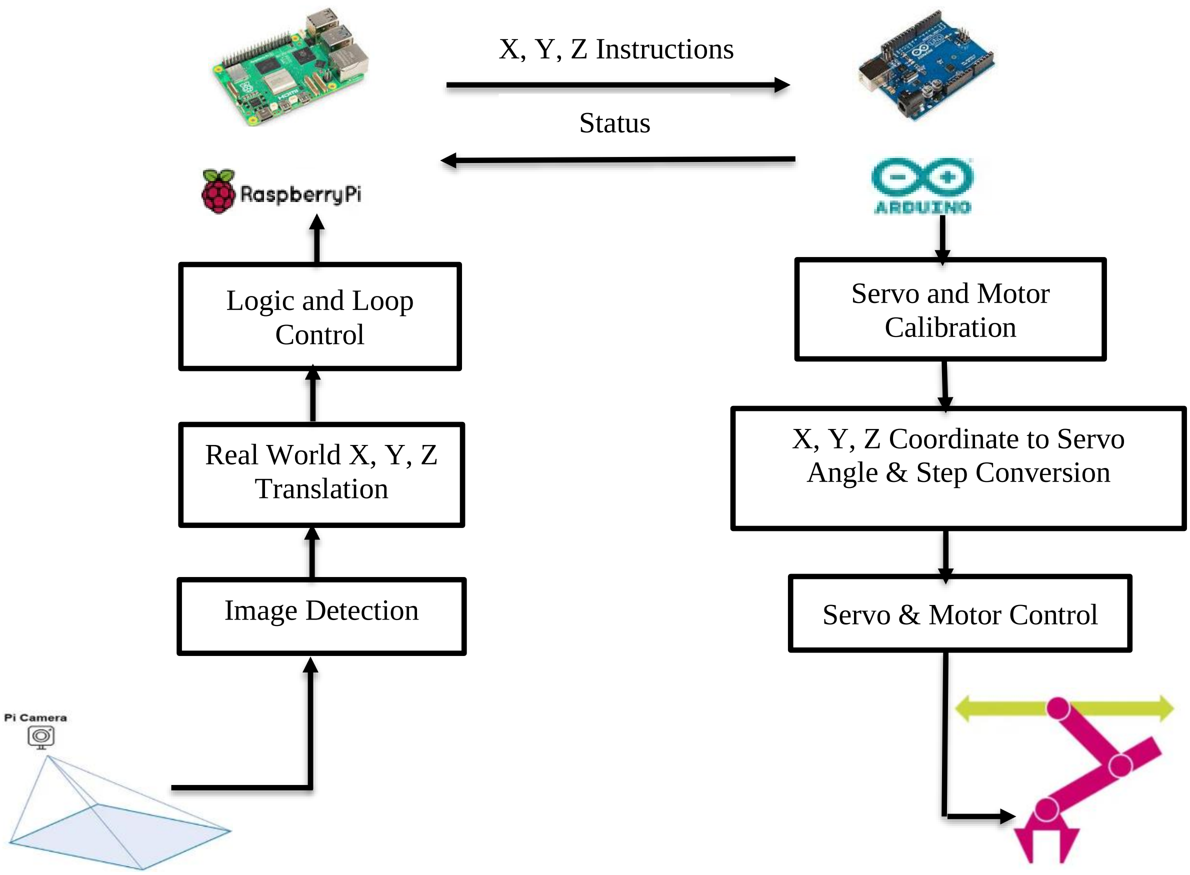

Figure 3.5 Work Flow of Robotic Arm for Automated Silkworm Disease Detection and Isolation

The figure 3.5 demonstrates an intelligent, automated approach to detecting and isolating diseased silkworms using AI-based image processing and robotic actuation. The system is designed to integrate a Raspberry Pi and an Arduino, enabling seamless communication and coordination for real-time detection and removal of infected silkworms. The process begins with a Pi Camera capturing images of the silkworms from a top-down perspective. These images undergo image processing on the Raspberry Pi, which identifies diseased silkworms based on predefined AI models. Once detected, the system translates the infected silkworm's position into real-world X, Y, and Z coordinates, ensuring precise localization. These coordinates are then transmitted to the Arduino, which acts as the robotic controller for the isolation mechanism. On the Arduino side, a servo and stepper motor calibration process ensures smooth actuation of the robotic arm.

The received coordinates are converted into the required servo angles and stepper motor movements to guide the robotic arm accurately. The arm, equipped with a gripper mechanism, carefully picks up the diseased silkworm and relocates it to an isolation zone.

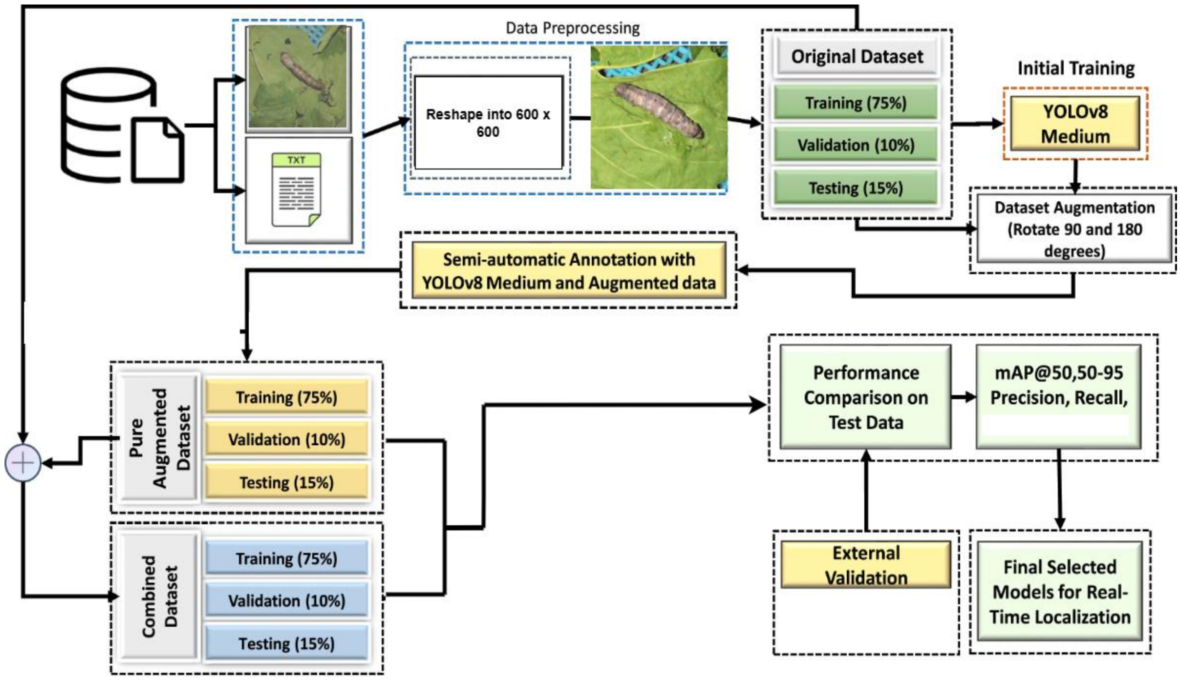

Figure 3.6 Proposed Framework for Data Collection, Pre-Processing, and Training

The proposed framework for silkworm disease detection enhances automated disease identification in sericulture using deep learning and image processing. It begins with data collection, where high-quality silkworm images are gathered and pre-processed by resizing to 600 × 600 pixels for consistency. Text-based annotations mark diseased silkworms using a semi-automatic YOLOv8 Medium approach, ensuring precise bounding box placement while reducing manual effort. Data augmentation techniques like 90° and 180° rotations improve model generalization by increasing image diversity. The dataset is split into training (75%), validation (10%), and testing (15%) subsets for optimal model learning. Two dataset types are used: the pure augmented dataset, containing only artificially augmented images, and the combined dataset, which includes both original and augmented images. YOLOv8 Medium, known for its real-time efficiency, trains on both datasets. Model performance is evaluated using mean Average Precision (mAP) at IoU thresholds of 50 and 50-95, precision, and recall. A comparative analysis determines the most reliable model for accurate disease detection.

3.4 BLOCK DIAGRAM

The block diagram of the proposed system illustrates the seamless integration of AI-based image processing, robotic automation, and environmental control mechanisms for efficient silkworm disease management. The figure 3.7 consists of input, processing, and output modules, ensuring real-time identification and removal of infected silkworms. The input module includes a Pi Camera, which captures high-resolution images of silkworms in the rearing trays. These images are processed using a YOLOv8 deep learning model deployed on Raspberry Pi, classifying silkworms as healthy or diseased based on visual symptoms. The control unit, consisting of Arduino and Raspberry Pi, processes the AI-based classification results and sends commands to the robotic arm for precise removal of infected silkworms. The robotic arm operates using NEMA 17 stepper motors and servo motors, ensuring accurate pick-and-place functionality. A power supply and voltage regulators (LM2596, A4988 Stepper Driver) ensure stable operation of all components. The output module includes the robotic arm, stepper motors, and servo motors, which execute disease isolation by transferring infected silkworms into a separate containment area. Additionally, the system is designed to integrate environmental sensors for temperature and humidity monitoring, enhancing disease prevention. The entire setup enables real-time, automated disease identification, isolation, and monitoring, significantly reducing human intervention while improving productivity and silk yield in sericulture.

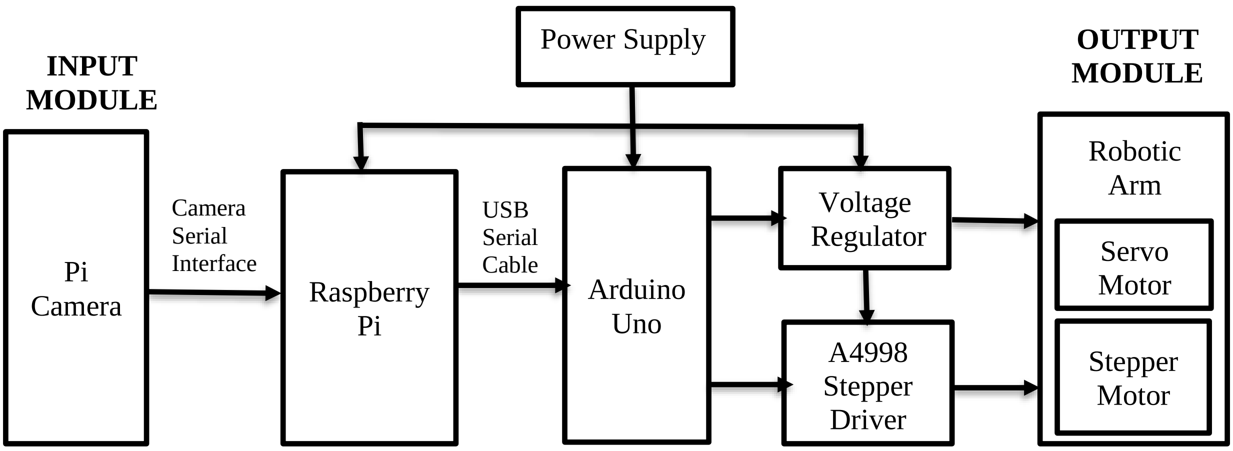

Figure 3.7 Block Diagram of Automated Sericulture Smart Grid

CHAPTER 4

SYSTEM SPECIFICATION

4.1 SOFTWARE REQUIREMENTS

The proposed system requires a combination of machine learning frameworks, microcontroller programming tools, and automation software to implement AI-based disease detection, robotic control, and system monitoring. The key software components include:

- Google Colab – Used for training and testing the YOLOv8 deep learning model for disease identification. It provides cloud-based GPU acceleration, enabling efficient image processing and model deployment.

- Roboflow – Facilitates dataset annotation, augmentation, and model training for YOLOv8-based silkworm disease classification. It helps in generating high-quality datasets for improving detection accuracy.

- Arduino IDE – Used for programming Arduino microcontrollers, which control servo motors, stepper motors, and sensor modules for robotic arm movement and environmental control.

- Raspberry Pi OS – The operating system for Raspberry Pi, responsible for running the YOLOv8 inference model, processing image data, and sending commands to the robotic arm.

- Serial Communication Software (PuTTY) – Helps in monitoring and debugging data exchange between Raspberry Pi, Arduino, and connected components.

- Onshape – CAD software for designing and simulating the robotic arm structure, ensuring optimal performance before implementation.

4.2 HARDWARE REQUIREMENTS

Arduino The hardware requirements encompass a suite of specialized sensor for monitoring the environment 24/7 and to provide real time data, complemented by a core controller for data processing and transmission. This setup facilitates real time data collection and analysis to ensure effective monitoring to detect any hazard from the industry.

- Arduino UNO Development Board
- Raspberry Pi 4
- Pi Camera
- NEMA 17 Stepper Motor
- Servo Motor (MG995)
- A4988 Stepper Motor Driver
- LM2596 Voltage Regulator
- Power Supply (SMPS / 12V DC Adapter)

4.3 HARDWARE DESCRIPTION

4.3.1 ARDUINO UNO

The Arduino Uno is a microcontroller board that serves as the control unit for managing the robotic arm, motors, and environmental automation in the proposed system. It receives commands from the Raspberry Pi via UART communication (RX: D0, TX: D1) after processing the YOLOv8 deep learning model for disease detection. Once an infected silkworm is identified, the Arduino controls the robotic arm’s movement using MG995 servo motors connected to PWM pins (D9, D10) for gripper and arm motion, and a NEMA 17 stepper motor connected via the A4988 driver module through digital pins (D4, D5) for linear displacement. Additionally, the Arduino regulates environmental conditions by managing temperature and humidity sensors and controlling actuators to maintain optimal rearing conditions. It is powered by a 5V power supply, ensuring real-time sensor data processing and motor control with minimal human intervention.

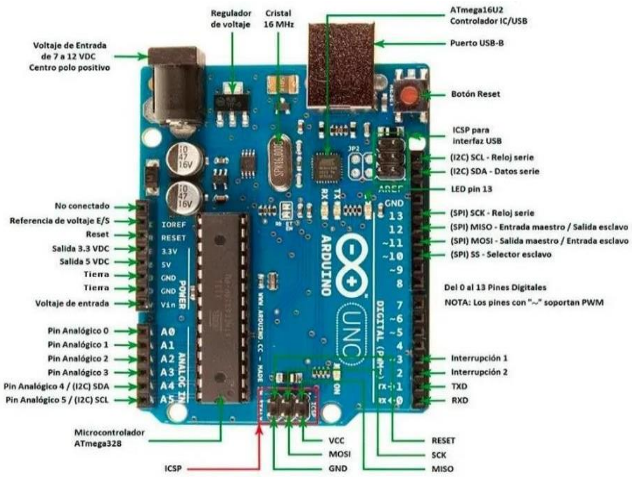

Figure 4.1 Arduino UNO

The Arduino Uno controls the robotic arm's movement and gripper operation in the silkworm disease detection system. It interfaces with a servo motor for the gripper, a stepper motor for linear motion, and a driver for precise control. The table 4.1 given below details its connections with other components.

Table 4.1 Connections of Arduino Uno

SI.NO	COMPONENT	ARDUINO UNO PIN	CONNECTION DETAILS
1.	Servo Motor (Gripper Control)	PWM Pin (D9)	Signal to control gripper movement
2.	Stepper Motor (Linear Movement)	Digital Pins (D2-D5)	Connected to stepper driver for arm motion
3.	Stepper Motor Driver	5V, GND, Digital Pins	Controls stepper motor operation
4.	Raspberry Pi	TX/RX (GPIO 8, GPIO10)	Serial communication for YOLOv8 image processing
5.	Power Supply	Vin, GND	Provides power to Arduino and connected motors

4.3.2 RASPBERRY PI 4

The Raspberry Pi is a compact yet powerful single-board computer that serves as the central processing unit in the proposed system. It is responsible for running the YOLOv8 deep learning model, processing real-time image data captured by the Pi Camera, and coordinating actions between various hardware components.

The AI based disease detection algorithm deployed on the Raspberry Pi classifies silkworms as healthy or diseased. Upon detecting an infection, the Raspberry Pi transmits control signals to the Arduino Uno via UART (TXD: GPIO14, RXD: GPIO15) to execute precise robotic arm movements for isolating the infected silkworms. Additionally, it interfaces with cloud storage or a local database to log disease detection data and track infection trends over time. Supporting Wi-Fi and Bluetooth, the Raspberry Pi enables remote monitoring and system updates. It operates on a 5V power supply, with GPIO pins used for additional interfacing. By managing high-speed AI computations, real-time monitoring, and control tasks, the Raspberry Pi plays a pivotal role in automating silkworm disease detection and isolation, significantly reducing manual labor while enhancing the efficiency and productivity of sericulture farms.

Figure 4.2 Raspberry Pi 4

The Raspberry Pi serves as the central processing unit for image capture, disease detection, and communication with the Arduino Uno. It connects to the Pi Camera for real-time image acquisition, processes data using the YOLOv8 model, and sends control signals to the Arduino for robotic arm operations. The table 4.2 given below details the connections.

Table 4.2 Connections of Raspberry Pi

SI.NO	COMPONENT	RASPBERRY PI PIN	CONNECTION DETAILS1.
1.	Pi Camera	CSI Interface	Captures images for disease detection
2.	Arduino Uno (RX)	GPIO 14 (TX)	Sends control signals for robotic arm operation
3.	Arduino Uno (TX)	GPIO 15 (RX)	Receives feedback from Arduino
4.	Stepper Motor Driver	GPIO 18	Controls stepper motor for linear movement

4.3.3 PI CAMERA

The Pi Camera is a high-resolution image sensor essential for capturing real-time images of silkworms to facilitate AI-based disease detection. Mounted in the rearing area, it continuously monitors silkworms and transmits image data to the Raspberry Pi via the CSI (Camera Serial Interface) port, where the YOLOv8 deep learning model analyzes the images to classify silkworms as healthy or diseased. The camera ensures detailed image acquisition, enabling the AI model to detect disease symptoms such as Flacherie, Pebrine, Grasserie, and Muscardine, based on color variations, body texture changes, and movement abnormalities. The Pi Camera's automated monitoring capability eliminates the need for manual inspection, providing a non-intrusive, real-time surveillance system that enhances early disease detection and timely intervention. Operating on a 5V power supply from the Raspberry Pi, the camera's seamless integration into the system significantly improves the accuracy, efficiency, and scalability of automated sericulture disease management.

Figure 4.3 Pi Camera

4.3.3 NEMA 17 STEPPER MOTOR

The NEMA 17 Stepper Motor is a high-precision motor responsible for controlling the linear movement of the robotic arm used in the automated removal of diseased silkworms. Once the YOLOv8 deep learning model detects an infected silkworm, the Raspberry Pi sends a control command to the Arduino Uno via UART, which then activates the NEMA 17 stepper motor through the A4988 stepper motor driver. The stepper motor is connected to the Arduino's digital pins (D4 for STEP, D5 for DIR, and D6 for ENABLE), enabling precise, incremental movements to position the robotic arm accurately without disturbing healthy silkworms.

Unlike traditional motors, the NEMA 17 stepper motor provides superior control over positioning, making it ideal for delicate pick-and-place operations. Its high torque and stability ensure smooth and accurate movement, minimizing errors in diseased silkworm removal. By enabling automated, precise robotic motion, the NEMA 17 stepper motor significantly enhances the efficiency, accuracy, and reliability of the disease management system in sericulture..

Figure 4.4 NEMA 17 Stepper Motor

4.3.3 SERVO MOTOR (MG995)

Servo motors play a crucial role in the precise movement and control of the robotic arm, enabling accurate gripping and placement of diseased silkworms. Once the YOLOv8 deep learning model detects an infected silkworm, the Raspberry Pi sends a control command to the Arduino Uno via UART, which then activates the servo motors to position the robotic arm and operate the gripper mechanism. The MG995 servo motors, connected to the Arduino’s PWM pins (D9 and D10), allow for precise angular movement, ensuring the robotic arm gently picks up diseased silkworms without harming the healthy ones. Servo motors ensure smooth and controlled motion, preventing sudden jerks that could disrupt the rearing environment. They are also highly energy-efficient and responsive, making them ideal for automated disease removal tasks. By enabling accurate and efficient robotic manipulation, servo motors enhance the precision, speed, and reliability of the silkworm disease management system, minimizing human intervention and ensuring a healthier rearing environment.

Figure 4.5 Servo Motor

4.3.4 STEPPER MOTOR DRIVER (A4988)

The A4988 Stepper Motor Driver is a high-performance motor controller that regulates the NEMA 17 stepper motor’s movement, ensuring precise operation of the robotic arm for diseased silkworm removal. Once the YOLOv8 deep learning model detects an infected silkworm, the Raspberry Pi sends a control command to the Arduino Uno via UART, which then activates the A4988 driver to adjust the stepper motor’s speed and position accurately.

This driver is connected to the Arduino’s digital pins (D4 for STEP, D5 for DIR, and D6 for ENABLE), allowing step-by-step movement of the robotic arm to accurately pick and isolate diseased silkworms without disturbing healthy ones. The A4988 provides adjustable micro-stepping control, enhancing precision and stability in silkworm handling. Additionally, it includes overcurrent and thermal protection, ensuring safe and reliable operation of the robotic system. By delivering precise motor control, optimizing power consumption, and enhancing movement accuracy, the A4988 Stepper Motor Driver plays a crucial role in automating silkworm disease management, significantly improving efficiency and reducing manual labor in sericulture farms.

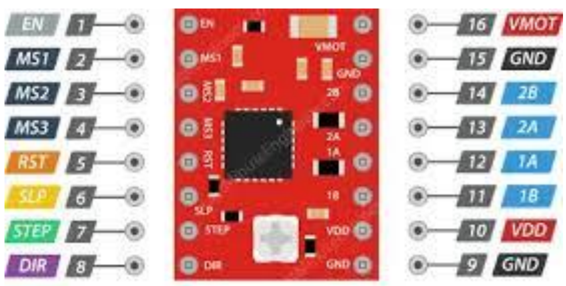

Figure 4.6 A4988 Stepper Motor Driver

4.3.5 VOLTAGE REGULATOR (LM2596)

The LM2596 Voltage Regulator is a crucial power management component that ensures a stable and efficient power supply for all electronic components in the system. It steps down higher input voltages (12V or 24V) to the required 5V or 3.3V, preventing power fluctuations that could damage sensitive components like the Raspberry Pi, Arduino Uno, stepper motors, and servo motors. The regulator is connected with VIN receiving 12V from the power supply, VOUT providing 5V output to the Raspberry Pi and Arduino, and GND linked to the common ground. This ensures uninterrupted power delivery, improving efficiency and longevity while maintaining system stability for smooth robotic arm movement, image processing, and disease detection. By providing regulated and reliable voltage, the LM2596 plays a vital role in the safe and efficient operation of the automated silkworm disease management system.

Figure 4.7 LM2596 Voltage Regulator

4.3.6 POWER SUPPLY (SMPS)

The Power Supply (SMPS) ensures consistent and reliable power distribution to all electronic and mechanical components in the system. The 12V DC adapter directly powers the stepper motor and A4988 driver, while the LM2596 voltage regulator steps down 12V to 5V for the Raspberry Pi, Arduino Uno, and Pi Camera. The servo motors (MG995) require 6V, which is regulated through the Arduino's PWM pins.

The GND of all components is connected to a common ground, ensuring circuit stability and preventing voltage fluctuations. This setup enables smooth operation of the robotic arm, AI-based disease detection, and automated silkworm isolation, maintaining the system's efficiency and longevity.

Figure 4.8 SMPS

4.4 PIN CONFIGURATION

Efficiently configuring the Pi Camera, motors, and sensors on the Raspberry Pi and Arduino Uno is crucial for accurate disease detection, seamless robotic arm control, and efficient silkworm isolation. Understanding the pin assignments and voltage requirements ensures smooth integration of hardware components, enabling precise silkworm monitoring and robotic intervention.

Table 4.3 Components PIN Configuration

SI.NO	**COMPONENTS**	**PROCESSOR INTERFACE**	**PIN CONFIG**	**APPLIED VOLTAGE**
1)	Arduino Uno	Raspberry Pi	TX (Pi) → RX (Arduino), RX (Pi) → TX (Arduino), GND→ GND	5V (via USB)
2)	Pi Camera Module	Raspberry Pi	CSI Port	3.3V
3)	SG90 Servo (Gripper Control)	Arduino Uno	PWM D11	5V-6V (External Power Source)
4)	MG995 Servo (Left Arm Control)	Arduino Uno	PWM D9	5V-6V (External Power Source)
5)	MG995 Servo (Right Arm Control)	Arduino Uno	PWM D9	5V-6V (External Power Source)
6)	Stepper Motor (Arm Linear Motion)	Arduino Uno (via A4988)	DIR → D4, STEP → D5, ENABLE → D6	12V
7}	A4988 Stepper Motor Driver	Arduino Uno	VCC → 5V, GND → GND, DIR → D4, STEP → D5, ENABLE → D6	12V Motor Supply, 5V Logic Supply

Table 4.3 provides a comprehensive overview of the hardware interfacing in the automated silkworm disease detection and isolation system. The integration of the Arduino Uno and Raspberry Pi ensures seamless communication between various components, enabling real-time image processing and robotic control for diseased silkworm identification and removal. The Arduino Uno is responsible for controlling servo motors and stepper motors, while the Raspberry Pi acts as the primary processor, handling image analysis using the YOLOv8 model. The communication between the Raspberry Pi and Arduino Uno is established via serial TX and RX pins, allowing for command exchange. The Pi Camera, connected through the CSI port, captures live images of silkworms, which are analyzed for disease detection.

Servo motors, including the SG90 for gripper control and MG995 for arm movements, are connected to the PWM pins of the Arduino Uno (D9 and D11). These motors play a crucial role in manipulating the robotic arm to isolate diseased silkworms. Additionally, a stepper motor is employed for linear arm movement, interfaced with the Arduino Uno via an A4988 motor driver. The A4988 driver, powered by a 12V supply, controls the stepper motor through DIR, STEP, and ENABLE pins, ensuring precise positioning. The applied voltage section of the table highlights the power requirements of each component. The Arduino Uno is powered via a 5V USB supply, while the Pi Camera operates at 3.3V. Servo motors require an external 5V–6V power source, ensuring sufficient torque for smooth robotic arm operations. The stepper motor and A4988 driver demand a 12V motor supply, along with a 5V logic supply for signal processing.

Table 4.3 serves as a critical reference for understanding the electrical connections and power distribution within the project, ensuring efficient functionality of the automated system. Proper pin configurations and voltage management are essential for stable operation, reducing the risk of component damage and ensuring accurate silkworm disease detection and isolation.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 3D MODEL DESIGN

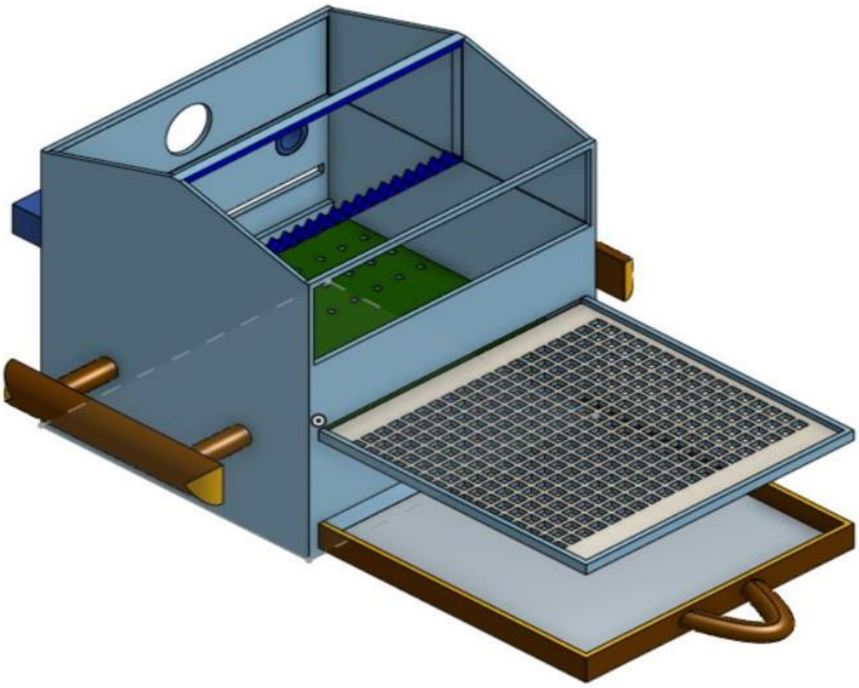

Figure 5.1 Figure of 3D Model Design

The 3D model of the proposed system showcases the strategic placement and integration of key components for automated silkworm disease detection and isolation. A robotic arm is centrally positioned to perform precise pick-and-place operations, while a Pi Camera is mounted in the top corner to capture images of the silkworms. The image acquisition process occurs twice daily, in the morning and evening, ensuring continuous monitoring of silkworm health. The captured images are processed using a trained deep learning model deployed on Google Colab, where the system classifies silkworms as healthy or diseased. If an infected silkworm is detected, the robotic arm is activated to isolate it, preventing further contamination within the batch. This automated workflow enhances accuracy, minimizes human intervention, and improves disease management efficiency in sericulture farms.

5.2 YOLOv8 MODEL OUTPUT

Figure 5.2 Detection of Diseased Silkworm using YOLOv8 Model

The images illustrate the application of a YOLOv8-based deep learning model for automated silkworm disease detection. The model has been trained on a dataset consisting of 14,048 images, with 75% (12291 Images) allocated for training, 15% (**1171** Images) for validation, and 10% (**586** Images) for testing. This extensive dataset includes both healthy and diseased silkworms, enabling the model to classify and identify infected silkworms with high accuracy. The bounding boxes in the images indicate the detected unhealthy silkworms, with corresponding confidence scores that reflect the probability of infection.

From figure 5.2, in the first image, a single diseased silkworm is identified with an 88% confidence level, highlighting its clear symptoms of infection. From figure 5.2, in which the second image shows multiple silkworms, with varying degrees of infection, classified with different confidence levels (33% to 59%). The trained YOLOv8 model successfully distinguishes between healthy and diseased silkworms, enabling early detection and intervention.

This automated detection system eliminates the need for manual inspection, reducing labour-intensive efforts and improving accuracy. The real-time analysis ensures that infected silkworms are identified promptly, preventing the spread of disease to healthy larvae. Once a diseased silkworm is detected, it is isolated using a robotic arm, enhancing the efficiency of the sericulture process and minimizing losses.

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Figure 5.3 Detection of Healthy Silkworm using YOLOv8 Model

The figure 5.3 showcases the detection and classification of healthy silkworms using a YOLOv8-trained deep learning model. The model accurately identifies the silkworms as "Healthy" with confidence scores of 88% and 92%, respectively, displaying bounding boxes around the detected subjects. Trained on a diverse dataset of both healthy and unhealthy silkworms, the YOLOv8 model processes images captured by a strategically positioned Pi camera to monitor silkworm health in real time. This automated detection system helps sericulture farmers by reducing manual labour, minimizing human errors, and enabling early disease identification. Healthy silkworms continue their growth cycle, while infected ones are swiftly isolated using a robotic arm, preventing disease spread and ensuring high-quality silk production. By integrating AI-based monitoring, this approach enhances disease prevention strategies, optimizes productivity, and contributes to a more sustainable and efficient sericulture process.

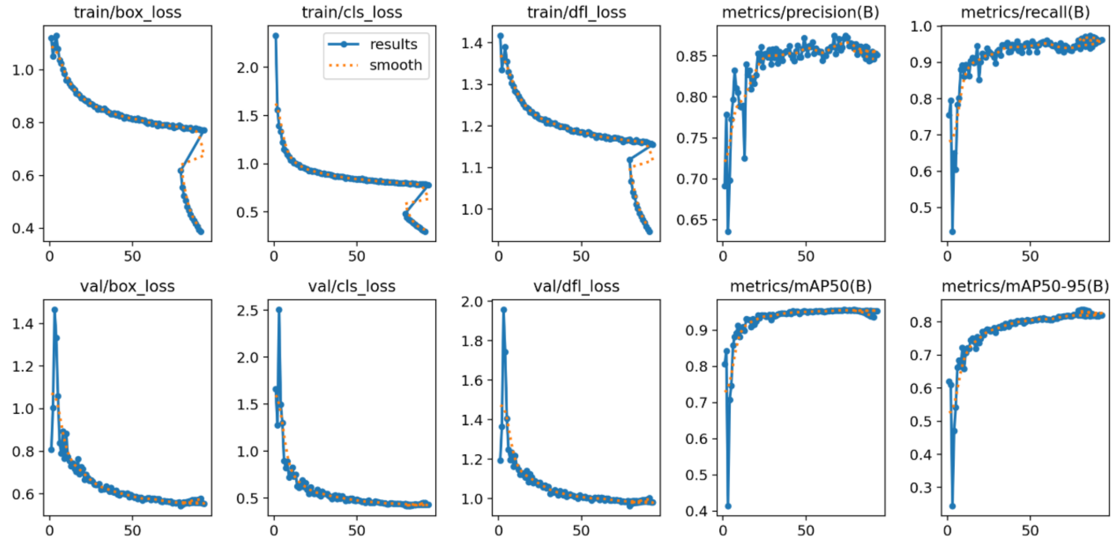

Figure 5.4 Training Performance Metrics of YOLOv8 Model

The above figure 5.4 represents the training progress of the YOLOv8 model used for silkworm health classification. It consists of eight subplots, displaying different loss functions and performance metrics over training epochs.

1. Loss Functions (Top-Left Three Graphs - train/box_loss, train/cls_loss, train/dfl_loss)
    - The box loss measures the accuracy of bounding box predictions, gradually decreasing as the model improves its localization capabilities.
    - The classification loss (cls_loss) evaluates the accuracy of the silkworm classification, showing a downward trend, indicating enhanced class separation between healthy and diseased silkworms.
    - The distribution focal loss (dfl_loss), used in bounding box regression, also decreases consistently, signifying the model's increasing confidence in its predictions.
2. Validation Losses (Bottom-Left Three Graphs - val/box_loss, val/cls_loss, val/dfl_loss)
    - These losses indicate the model's performance on unseen validation data. The decreasing trends in validation losses demonstrate that the model generalizes well without significant overfitting.

3. Performance Metrics (Top-Right Three Graphs - precision, recall, and mAP scores)
    - Precision (metrics/precision(B)) improves steadily, reflecting fewer false positives in detection.
    - Recall (metrics/recall(B)) also increases, meaning the model successfully identifies a higher proportion of actual positive instances (i.e., healthy and diseased silkworms).
    - Mean Average Precision (mAP50 and mAP50-95): The mAP50 score reaches above 0.9, indicating high detection accuracy for IoU thresholds above 50%. The mAP50-95 metric, which averages precision across multiple IoU thresholds, also improves steadily, confirming robust object detection across varying conditions.

5.3 DEMO PROTOTYPE

The robotic arm model is a critical component of the Automated Silkworm Disease Identification and Isolation System, designed to efficiently remove diseased silkworms from healthy populations. The arm is integrated with AI-based image processing technology using the YOLOv8 model to detect infected silkworms and ensure precise pick-and-place operations. The robotic arm consists of multiple degrees of freedom, allowing it to navigate the silkworm-rearing trays with high accuracy. It operates based on coordinate-based control, where X, Y, and Z-axis translations are mapped to servo and stepper motor movements. The arm is equipped with NEMA 17 stepper motors for precision control and servo motors for fine adjustments. The control system is managed through an Arduino Uno and Raspberry Pi, which process image data and send movement instructions.

When an infected silkworm is identified, the robotic arm is activated to isolate it by picking it up and placing it in a designated containment area. This automation significantly reduces manual labor, enhances disease management, and prevents further spread of infections like Pebrine, Flacherie, Grasserie, and Muscardine. By integrating AI, robotics, and real-time image detection, this prototype demonstrates an efficient, scalable solution for improving sericulture productivity.

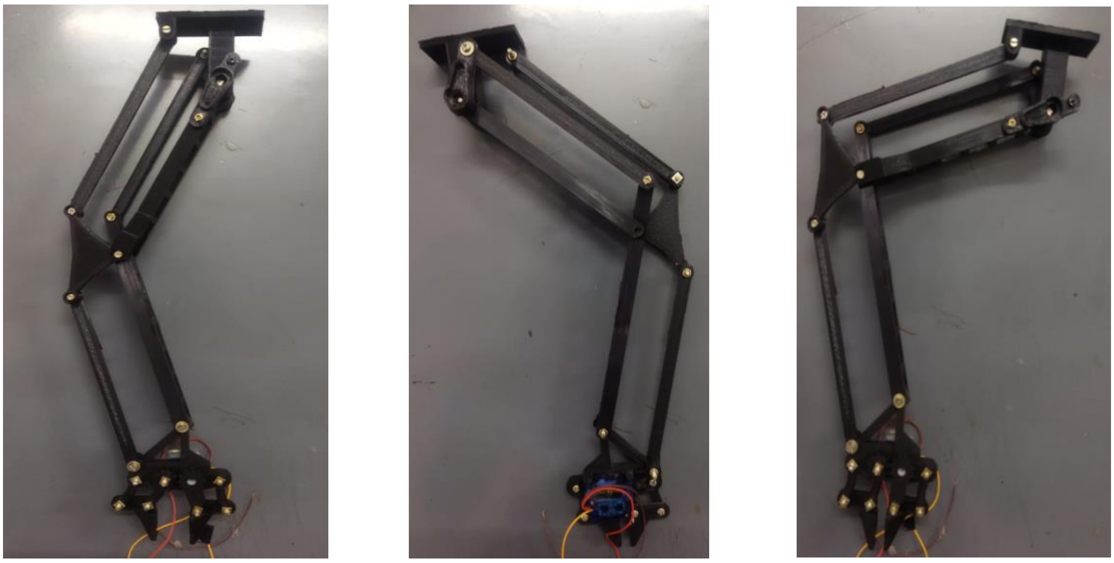

Figure 5.5 Figure of Designed Arm Model

The robotic arm depicted in the figure 5.5 is a 3D-printed, articulated mechanism designed for precise object manipulation, making it suitable for automation and robotic applications. Its structure consists of multiple interconnected joints, allowing for a range of controlled movements. The gripper mechanism is powered by a standard servo motor, enabling it to grasp and release objects with precision. Meanwhile, the MG995 high-torque servo motor is responsible for the vertical movement of the arm, providing stability and controlled motion for lifting and lowering operations. The arm's design incorporates a parallelogram linkage system, ensuring synchronized movement across joints for enhanced accuracy. The components are securely assembled using metal fasteners, improving the overall rigidity and durability of the structure. The electrical wiring is carefully routed to connect the servos to a microcontroller, which can be programmed for automated operations such as sorting, picking, and placing objects.

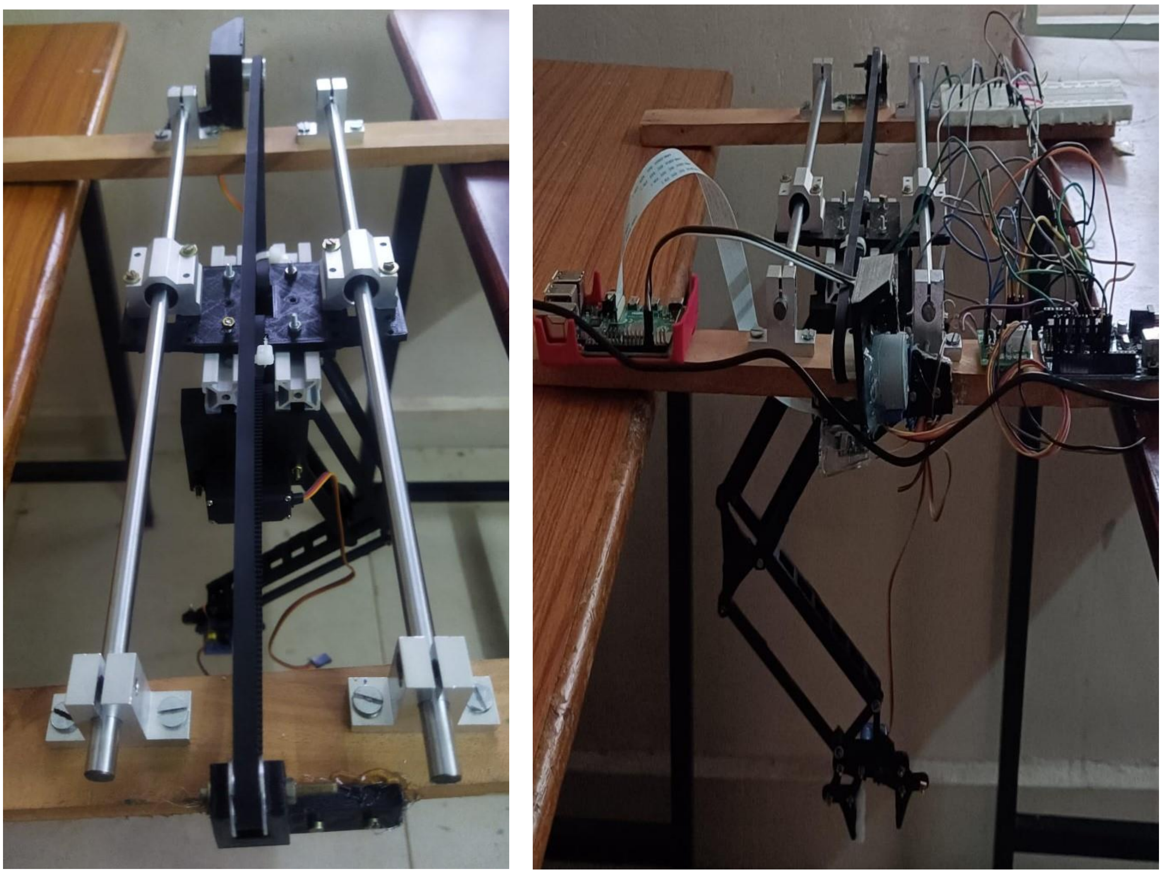

Figure 5.6 Motion Mechanism for Robotic Arm Positioning

The figure 5.6 showcases a high-precision belt-driven linear motion system, which is a crucial component of an AI-integrated robotic arm used for automated pick-and-place operations. The system is designed to facilitate smooth and accurate movement along a defined axis, ensuring efficient positioning of the robotic arm in various industrial and research applications. The core mechanism consists of two parallel metal guide rails, providing structural stability and allowing the robotic assembly to move along a fixed path. A stepper motor is employed to drive the belt mechanism, enabling controlled linear motion with high accuracy. The timing belt ensures synchronized movement along the rails, making it suitable for tasks requiring repetitive and precise displacements. Unlike servo motors, which are used for angular movements, the stepper motor ensures controlled incremental movement, making it ideal for applications demanding positional accuracy.

In addition to the stepper motor, a servo motor is utilized for pick-and-place operations, as well as vertical (up and down) movements of the robotic arm. The servo motor offers fine-tuned control over angular positioning, ensuring the gripper can accurately grasp, lift, and release objects. The robotic arm, mounted onto this linear motion system, enables smooth transitions between different positions while maintaining stability and precision.
The structural components, including the 3D-printed mounting brackets and metal support frames, enhance the durability and rigidity of the system. The bearing-based sliding mechanism ensures minimal friction and wear, improving the longevity and efficiency of the setup. This system is particularly advantageous in fields such as automated sericulture, AI-based material handling, object sorting, and precision assembly. By integrating AI-based image processing and automated decision-making, this robotic system is capable of performing real-time object identification and isolation. This makes it an ideal solution for applications requiring intelligent automation, such as silkworm disease identification and isolation, where precision and efficiency are critical.

The robotic arm in the Automated Sericulture Smart Grid efficiently detects and isolates diseased silkworms using AI-based image processing. A Pi Camera captures real-time images of silkworm trays, which are analyzed using a YOLOv8 deep learning model to accurately classify healthy and diseased silkworms. Once detected, the system maps the coordinates of the diseased silkworm and directs the robotic arm using a stepper motor-driven belt system for linear movement and servo motors (MG995) for precise pick-and-place operations. The gripper, controlled by a servo motor, carefully picks up the diseased silkworm and transfers it to an isolated chamber. The system achieves high accuracy (mAP > 90%), ensuring efficient removal without disturbing healthy silkworms. This AI-driven automation reduces manual labor, enhances disease management in sericulture, and improves overall productivity.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

In conclusion, this project successfully integrates AI-based image processing and robotic automation to enhance disease detection and isolation in silkworm farming. The use of YOLOv8 for real-time classification and a robotic arm with precise pick-and-place mechanisms ensures accurate removal of diseased silkworms, minimizing the risk of contamination. By reducing manual intervention and improving disease management efficiency, this system significantly contributes to the overall productivity and sustainability of sericulture. The combination of computer vision and robotic automation not only enhances efficiency but also reduces labour costs, ensuring a more scalable and cost-effective approach for sericulture farmers.

Future advancements include multi-camera setups for enhanced detection accuracy, faster deep-learning models for real-time processing, and adaptive grippers for handling silkworms of different sizes. IoT-based monitoring can enable remote disease tracking, while automated feeding mechanisms can further optimize farming efficiency. Additionally, self-learning AI models that adapt to new disease patterns will improve reliability for large-scale applications. With the advent of YOLOv9, YOLOv10, YOLOv11, and YOLOv12, future models will offer higher accuracy, faster inference, and improved adaptability to disease variations. Integrating these advanced models with cloud-based data analytics will provide predictive insights into disease outbreaks, allowing for early intervention. In the long run, combining AI-driven monitoring with biotechnology innovations, such as genetic disease resistance in silkworms, can further revolutionize sericulture, ensuring a more resilient and efficient farming system.

REFERENCE

[1] G. R. Poornima, F. Taj, T. M. Gavinya, G. Madhu, and B. N. Madhubala, "Arduino Based Automated Sericulture System," in Proc. 2018 3rd IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT), 2018.

[2] M. A. Dixit, A. Kulkarni, N. Raste, and G. Bhandari, "Intelligent control system for sericulture," in Proc. 2015 Int. Conf. Pervasive Comput. (ICPC), IEEE, 2015.

[3] S. S. Devi, S. Gadde, K. Harish, C. Manoharan, R. Mehta, and S. Renukadevi, "IoT and image processing Techniques-Based Smart Sericulture Nature System," Indian J. Appl. Pure Bio., vol. 37, no. 3, pp. 678-683, 2022.

[4] Bio, Pure. "IoT and image processing Techniques-Based Smart Sericulture Nature System." Indian J. Applied & Pure Bio. Vol 37, no. 3 (2022): 678-683.

[5] A. Yudhana, "Tsukamoto fuzzy inference system on Internet of Things-based for room temperature and humidity control," IEEE Access, vol. 11, pp. 6209-6227, 2023.

[6] S. Jyothi, D. M. Mamatha, P. J. Raju, S. Sultana, and J. Seetharamulu, "A Study on the Sericulture Farm Automation System Using the Internet of Things (IoT)," in Proc. 2nd Int. Conf. Comput. Bio Eng. (CBE), Springer, 2021.

[7] Z. Dong, X. Li, Z. Li, and Y. Hou, "Modeling simulation and temperature control on thermal characteristics of airborne liquid cooling system," IEEE Access, vol. 8, pp. 113112-113120, 2020.

[8] N. S. Yogeshraj, N. Thamilarasi, S. Sailaja, C. Poonguzhali, and S. Kannagi, "Smart automated sericulture based on image processing technique and embedded system," J. Univ. Shanghai Sci. Technol., vol. 24, no. 1, pp. 327-331, 2022.

[9] M. Nivaashini, R. S. Soundariya, and A. D. Kumar, "Silkworm growth monitoring smart sericulture system based on IoT and image processing," Int. J. Comput. Appl., vol. 975, p. 8887, 2018.

[10] S. Nojiri, T. Nishimura, K. Tadakuma, and T. Watanabe, "Flexible and slim device switching air blowing and suction by a single airflow control," IEEE Robot. Autom. Lett., vol. 8, no. 5, pp. 2637-2644, 2023.

[11] S. Rokhade, M. K. Guruprasad, M. S. Mallesh, S. Banu, S. N. Jyoti, and D. Thippesha, "Smart sericulture system based on IoT and image processing technique," in Proc. 2021 Int. Conf. Comput. Commun. Informatics (ICCCI), IEEE, 2021.

[12] I. S. Jahnavi, S. S. Vamsi, B. Akhil, K. R. Reddy, and R. Ramalakshmi, "Silkworm incubator," in Proc. 2023 4th Int. Conf. Intell. Eng. Manage. (ICIEM), IEEE, 2023.

[13] A. Lee, G. Kim, S. J. Hong, S. W. Kim, and G. Kim, "Classification of dead cocoons using convolutional neural networks and machine learning methods," IEEE Access, vol. 11, pp. 137317-137327, 2023.

[14] B. U. Adarsh, H. J. Shivayogappa, and K. N. Navya, "Automated smart sericulture system based on 6LoWPAN and image processing technique," in Proc. 2016 Int. Conf. Comput. Commun. Informatics (ICCCI), IEEE, 2016.

[15] Z. Zhu et al., "High-speed sex identification and sorting of living silkworm pupae using near-infrared spectroscopy combined with chemometrics," Sens. Actuators B Chem., vol. 268, pp. 299-309, 2018.

[16] P. P. Prasobhkumar, C. R. Francis, and S. S. Gorthi, "Automated quality assessment of cocoons using a smart camera-based system," Eng. Agric. Environ. Food, vol. 11, no. 4, pp. 202-210, 2018.

[17] M. C. Ramya, V. Lokesh, T. N. Manjunath, and R. S. Hegadi, "A predictive model construction for mulberry crop productivity," Procedia Comput. Sci., vol. 45, pp. 156-165, 2015.

[18] B. Srinivas, K. Kumari, H. Goverdhan Reddy, N. Niranjan, S. A. Hariprasad, M. P. Sunil, "IoT Based Automated Sericulture System," Int. J. Recent Technol. Eng. (IJRTE), vol. 8, no. 2, 2019.

[19] K. Eethamakula, K. S. Charan, G. V. S. Raju, E. V. Kumar, K. Y. Babu, M. Naveen, "Automatic Detection, Controlling, and Monitoring of Temperature in Sericulture Using IoT," IJAEMA, vol. 12, pp. 1099-1103, 2020.

[20] V. Mekala, K. S. Tamilsehan, V. M. Vinod, S. Balambigai, J. Kousalya, K. Medhini, R. Nandhini, "Internet of Things-Based Innovative and Cost-Effective Smart Sericulture Farm Incubator," in Proc. 2021 5th Int. Conf. Electron. Commun. Aerosp. Technol. (ICECA), IEEE, 2021.

[21] A. Farooq, "The Convergence of IoT and Image Processing in Sericulture: An Overview of Innovative Applications," Int. J. Soc. Anal., vol. 8, no. 6, pp. 16-35, 2023.

[22] B. N. Gnanesh, G. S. Arunakumar, A. Tejaswi, M. Supriya, A. Pappachan, M. M. Harshitha, "Molecular Diagnostics of Soil-Borne and Foliar Diseases of Mulberry: Present Trends and Future Perspective," in The Mulberry Genome, Cham: Springer, 2023, pp. 215-241.

[23] A. P. Ashwini, B. U. Adarsh, N. C. Hima, J. Likitha, S. B. Padashetty, S. Deshpande, "Design and Development of IoT-Based Smart Sericulture Plant," in Proc. 2024 8th Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solutions (CSITSS), IEEE, 2024.

[24] S. R. Suthar, S. Devaraj, M. R. Maanasa, K. V. Vidya, N. Siby, B. R. Revanna, "Silk Shield: Empowering Sericulture with AI-Driven Disease Detection," in Proc. 2024 8th Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solutions (CSITSS), IEEE, 2024.

[25] D. A. Kumari, G. Moneekha, P. N. Sree, P. J. S. Ranjani, S. Neenasri, "Digital Farming for Silkworms: A Technological Breakthrough," in Proc. 2024 5th Int. Conf. Mobile Comput. Sustain. Informatics (ICMCSI), IEEE, 2024.