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Integration of Bangla Voice-Controlled Farming Robot with Convolutional Neural Networks for Smart Agricultural Applications

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Attestation

We understand what plagiarism is and how strict the university's anti-plagiarism policy is. This is our original work, we attest to that. Additionally, any third-party software or text included in this project is properly cited and compliant with well recognized academic standards.

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Acknowledgement

We commence by offering our heartfelt gratitude to the Almighty Allah for endowing us with the fortitude, perseverance and capability to diligently embark on and successfully complete our senior project. Our profound gratitude extends to Dr. Mohammad Shidujaman, our esteemed Supervisor, Assistant Professor of Independent University Bangladesh. His invaluable guidance, boundless patience and devoted investment of time have been instrumental in steering us through the intricacies of our project journey and shaping the formulation of this comprehensive report. Under their expert tutelage, our project progressed seamlessly and their insightful counsel proved indispensable at every juncture.

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We extend our deepest gratitude to Independent University Bangladesh for their exceptional senior project program. It has been instrumental in building our skills and equipping us for the demands of the research industry. Their support has developed our academic and professional journeys, and we are truly grateful for that.

Letter Of Transmittal

Dr. Mohammad Shidujaman
Senior Project Supervisor
Assistant Professor
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Subject: Senior Project Report on “Integration of Bangla Voice-Controlled Farming Robot with Convolutional Neural Networks for Smart Agricultural Applications”

Dear Sir,

We are truly honored to share our senior project report on “Integration of Bangla Voice-Controlled Farming Robots with Convolutional Neural Networks for Smart Agricultural Applications” with you. Working on this project under your supervision has been an incredible experience, teaching us so much about Robotics while bringing our vision of a smarter Agriculture System to Life. Our project with its design and complete development reflects the skills we have learned and the late night efforts we poured into making it work. Your constant support, insightful feedback and encouragement kept us going and we are thankful for that. We hope this report captures the heart of our project and meets your expectations. It’s been a pleasure to learn from you throughout the semesters.

Yours sincerely,

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List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
ASR	Automatic Speech Recognition
BDT	Bangladeshi Taka
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DL	Deep Learning
ESP32	Embedded Serial Peripheral 32-bit Microcontroller
ESDNN	Enforced Stacked Deep Neural Network
GLCM	Gray Level Co-occurrence Matrix
GPU	Graphics Processing Unit
GPS	Global Positioning System
GUI	Graphical User Interface
HCI	Human Computer Interaction
HRI	Human Robot Interaction
IoT	Internet of Things
KNN	K-Nearest Neighbors
ML	Machine Learning
NLP	Natural Language Processing
OMCNN	Optimal MobileNet Convolutional Neural Network
RAM	Random Access Memory
RGB	Red Green Blue Color Model
SLAM	Simultaneous Localization and Mapping
SVM	Support Vector Machine
TTS	Text To Speech
VGG	Visual Geometry Group(Deep Learning Model)
YOLO	You Only Look Once (Object Detection Algorithm)
SDG	Sustainable Development Goals

Abstract

Since the dawn of human civilization, agriculture has been the foundation of human civilization as it has been the basic ingredient to food security, economic growth, and societal development. However, the old practices of farming that have been in use over the centuries are becoming insufficient in meeting the needs of contemporary society. The farmers in most regions of the globe and especially in the developing countries such as Bangladesh are faced with numerous issues: disease of crops, unpredictable weather, lack of labor, inefficient irrigation, and lack of accessibility to agricultural education in time. These issues lead to low production, financial instability and food insecurity.

The blistering development of technology, in particular, robotics, artificial intelligence (AI), computer vision, and natural language processing (NLP), provide new opportunities to make agriculture a smarter, more efficient, and sustainable process than it has ever been. One of these solutions is the combination of Bengali voice-controlled Farming robots that have convolutional neural networks (CNNs) in identifying plant diseases and managing the farm. These systems transcend the level of mechanization to provide intelligent, context-aware, and farmer-friendly support.

The project under this is called the Integration of Bangla Voice-Controlled Farming Robot with Convolutional Neural Networks to Smart Agricultural Applications, which will focus on designing, developing, and testing a low cost agricultural robot, which in this case will be termed as AGRIBOT. AGRIBOT is a smart robot with AI-based leaf disease detection and Bengali voice interaction with robotic capabilities to perform basic tasks (irrigation and spraying). The robot can take the commands in both the Bangla and English language and processes the commands through speech recognition devices, and analyzes the crop health using CNN models, and provides actionable information to the farmers in their natural speech.

The approach to this project incorporates the hardware designing (Raspberry Pi, Arduino, sensors, motors, and pumps) and software development (Python, TensorFlow, OpenCV, NLP APIs, MySQL databases). CNN is trained on a set of mango leaf images with healthy and diseased samples, whereas the voice modules are optimized to the low-resource languages so that the Bangladeshi farmers can have access to it. Incorporating the human-centered design, surveys and interviews with the farmers were held, and their expectations of the appearance of the robot, its functionality, and the type of interaction with the robot were analyzed.

The project will not only bring a working prototype but also a research platform of multilingual agricultural robotics. It can be seen that the results of the study show that a voice-enabled AI robot enhances the accessibility of farmers, the time to respond to the disease outbreak, and the knowledge gap between rural populations. The AGRIBOT is an important advancement in the smart agriculture research despite the drawbacks that include the limitation of the dataset, the longevity of the hardware, and noise interference with the environment. The way to go in the future is cloud based data synchronization, support of other languages, IoT soil sensor integration, autonomous movement based on GPS and SLAM, and solar powered energy infrastructure.

To sum up, the present project confirms the applicability of the AI-powered voice-interactive farming robots in transforming the way farmers operate, allowing them to increase their productivity, and providing farmers with ready access to technological resources. GRIN does not just become a technical breakthrough, but is also a socially transformational innovation in line with the larger objective of the sustainable agricultural system, digital transformation, and inclusive rural development.

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CHAPTER 01

Introduction

1.1 Background

Agriculture has been the staple of human civilization since time immemorial, guaranteeing food security, economic stability and livelihoods of billions of people the world over. In the tropical regions like Bangladesh, agriculture is a major economic activity, which has a high number of people employed in the sector. Mango (Mangifera indica L.) is one of the numerous crops that are grown in this area and have a distinctive economic and cultural significance. It is a commercially important tropical fruit that is widely grown in the tropics and subtropics because of its nutritional content and demand in the market. Nevertheless, the quality and mango yield is also a significant issue since the foliar diseases including anthracnose, bacterial canker, and powdery mildew are common and greatly impact the production and fruit quality [1].

The conventional disease detection systems are very manual based whereby the farmers or agriculture experts would perform the manual inspections. Not only are such methods both time-consuming and labor intensive, but also subject to human error and inconsistencies especially when performed on a large-scale basis across orchards [2]. As a result, diseases may be diagnosed later or improperly identified, which will result in extensive crop losses, pesticides may be used ineffectively, and deterioration of soil in the long run. To meet these enduring issues, technological advancement has been incorporated more often into the field of agriculture to contribute to accuracy, effectiveness, and the sustainability of agriculture.

The latest developments in image processing, machine learning (ML), and deep learning (DL) have provided new opportunities in automatic and real-time diagnosis of plant disease. Specifically, Convolutional neural networks (CNNs) have proven to be very effective in classifying plant diseases in various datasets, which is better than other conventional methods of machine learning [3]. CNNs are capable of detecting diseases with an astonishing accuracy by using more intricate features of leaf images to detect them using computer vision methods, including texture, color gradients, shape patterns, and other features that are too complicated to detect through other methods [4], [5]. Such a change to automated visual inspection, as compared to manual inspection is a significant move to the modernization of agriculture.

Simultaneously, the application of Internet of Things (IoT) in agriculture has demonstrated intelligent farming systems that have the capability to collect, monitor, and make decisions in real-time [6]. The IoT and AI image processing technologies can also be used together to improve the overall management of the farm, with real-time disease detection and automated spraying systems that react instantly to the infection detected. These smart systems do not only reduce human intervention in repetitive activities but also help in making farming sustainable as they reduce the wastage of resources and maximize the use of pesticides and fertilizers [7].

This technological development has brought a new sphere called smart agriculture, where AI, IoT, and robotics collide to form solutions to agricultural issues on their own. In this respect, the present project proposes a CNN-based automatic mango leaf disease detector, which is expected to identify and categorize mango leaf diseases with high precision and incorporate with the automation hardware implemented on the IoT to execute a targeted spraying. This is because the system will use Raspberry Pi as the main processor with sensors, camera modules and microcontrollers that guarantee the system can respond and classify and detect diseases in real-time. Besides, the incorporation of the Bangla voice-based interaction that is inspired by the human-robot interaction model found in the AGRIBOT work, allows the farmers to naturally communicate with the system in their own language. This type of smart diagnosis, automation, and access are an indication of a holistic approach to precision agriculture in Bangladesh [8], [9].

1.2 Problem Statement

Foliar diseases are an annual major threat to the productivity of mango farming in Bangladesh. Threats which are common like Colletotrichum gloeosporioides (anthracnose), Xanthomonas campestris (bacterial canker) and Oidium mangiferae (powdery mildew) cause severe damages on mango leaves resulting in less fruit production, poor quality and significant economic losses in the domestic and export markets [2]. The traditional methods are very manual and ineffective and early detection of such diseases is necessary in order to manage them in a timely manner.

Traditional methods of detection mainly rely on human resource and thus are subject to inconsistency, exhaustion and error particularly during fluctuating weather patterns like fluctuating light or other intricate background patterns [3]. The close monitoring of the mango orchards by experts would not be possible in large orchards hence leading to late diagnosis,

spreading of the disease without control and an enormous use of pesticides which would harm the environment and interfere with the quality of the fruit products [7].

In spite of the fact that the application of deep learning methods, especially Convolutional Neural Networks (CNNs) recently shows high quality in the classification of plant diseases, the majority of current models are trained in controlled laboratory conditions using a homogeneous set of data [9]. In real-life scenarios, such systems tend to exhibit low accuracy because of the variability of natural images, such as variation in leaf angles, occlusion and lighting [3]. Studies have shown that, as much as CNNs are capable of achieving impressive accuracy, they are not as good at generalizing to the condition of a real farm environment [10].

The latest research has provided good outcomes regarding disease detection activities. Lightweight CNNs LeafNet, a model that was trained on MangoLeafBD dataset, predicted seven mango leaf diseases at an accuracy of 98.55%, indicating the potential of lightweight CNNs in agriculture [8]. On the same note, the accuracy of the Optimal MobileNet CNN (OMNCNN) model, by optimization of feature extraction and hyperparameter search, reached 98.7% in tomato leaf disease classification [11]. DenseNet-121, in its turn, achieved 90.81% accuracy on 38 categories of plant diseases, which is useful when analyzing diversity in a dataset, however, with its high computational needs cannot be deployed in the field [12].

It is however a big challenge to transfer these deep learning systems in the field as opposed to laboratory settings. An example of a robot that was not that successful is the RobHortic Spectral Imaging Field Robot which, though satisfactory in laboratory testing, dropped to 59.8% in the field (59.8% vs. 66.4% in the lab) demonstrating the challenge of performance maintenance under uncontrolled conditions [13]. In the same vein, Ngugi et al. have pointed out that datasets quality and diversity plays a pivotal role in ensuring real world performance of plant disease recognition systems [14].

The other inherent constraint of the current research in the field of farm automation is the lack of integration between disease detection and followed measures like spraying or irrigation. The current systems are mostly limited to diagnosis without further extension to include automatic responses or real time communication with the farmers. Further, these technologies tend to be expensive and industrial-level nanotechnology, and therefore, they cannot be used by smallholder farmers in developing nations such as Bangladesh [15]. Also, usability is further

diminished by language barriers due to the lack of a localized version of most of the available tools to support native-language communication, thus making them usable by rural farmers in large numbers [16].

Thus, the issues addressed by the present study are the following ones, which are interrelated:

1. The absence of automation with regards to the early detection of the disease and intelligent response systems towards mango production.

2. Poor cost and availability of farm inputs to smallholder farmers.

3. Lack of adaptability to heterogeneous real world farm settings of CNN-based systems.

4. Absence of user-friendliness and multi-language interfaces that can serve the local farmers of Bangladesh.

In order to address them, the proposed system combines a CNN based real-time detector model (MobileNetV2) with an IoT-controlled automated spraying and irrigation systems, and a bilingual (Bangla/English) farmer interface. The unified strategy will ensure an increased effectiveness of managing diseases, reduce the levels of misuse of pesticides, as well as a sustainable cultivation of mangoes via a low-cost, scalable, and ecologically friendly digital agriculture platform [17], [18], [19].

1.3 Significance and Scope

The **significance of the AGRIBOT** project can be explained by its integration of technological innovation, social importance, and economic value. Agriculture has been one of the most important but demanding sectors particularly in developing nations where farmers are common victims of crop diseases, technical illiteracy as well as inaccessibility to modern technologies. The project directly relates to these issues, and it proposes a low-cost, intelligent robotic system which is intended to provide assistance to farmers in real time.

1. **Early Disease Detection**

Late detection of plant diseases is one of the greatest issues in farming. Farmers tend to discover infections when they are already damaged, and hence yield low and incur more

expenses. AGRIBOT helps to solve this problem with the help of a **Convolutional Neural Network (CNN) based image analysis system** that is capable of identifying mango leaf diseases with high accuracy in captured images. AGRIBOT detects diseases at an early stage thus enabling farmers to take preventative measures to prevent the spread of the infection among trees or farms.

As an illustration, a farmer can only issue an order to the robot to scan the field, take a few pictures and inform him about the potential outbreak of diseases like **anthracnose**, **bacterial canker**, or **powdery mildew**. This real time feedback guarantees prompt decision making and cuts on the reliance of agricultural experts who might be inaccessible to remote locations.

2. **Accessible Interaction**

The multilingual voice interface is one of the most useful functions of AGRIBOT since farmers can converse with it using simple, natural language. Being one of the easy-to-use alternatives to the text-based menus, AGRIBOT offers many farmers who have a low level of literacy and experience with digital systems.

The interaction with the robot is also intuitive and culturally relevant as commands such as “গাছের পাতা চেক করো” (“Check the leaves”) or “রোগের রিপোর্ট দেখাও” (“Show the disease report”) allow farmers to communicate directly with the robot in either the **Bengali or English** language. This strategy ensures that technology is affordable to a far greater number of users particularly in the rural areas.

3. **Task Automation**

In addition to the detection of diseases, AGRIBOT will have the ability to carry out various farming activities due to the hardware integration of its **sensors**, **motors**, and **actuators**. It can be expanded to deal with tasks like **irrigation**, **spraying pesticides**, and **autonomous navigation** between rows of plants. AGRIBOT allows reducing the physical workload on farmers, as well as saving time, by automating these repetitive and labor-intensive tasks.

As an example, as long as it is tracking the conditions of diseases, the robot will be able to spray specific locations with the necessary treatments, which will guarantee precise farming and reduce the waste of chemicals.

4. **Low-Cost Scalability**

One factor that can lead to the usefulness of technology to the farmers is affordability. AGRIBOT is developed using **cost effective materials** like **Raspberry Pi**, **arduino**, **ESP32** and is affordable by small and medium scale farmers. These are the most common parts, simple to code, and use less power, meaning that the robot can be recreated or upgraded without incurring much expense in terms of financial consideration. The modular design is also scalable, i.e. additional sensors or functionalities can be added in future depending on the requirements of the farmer or particular crop.

5. **Sustainability**

Sustainability is at the heart of AGRIBOT's design. It facilitates the minimization of unnecessary consumption of fertilizer, pesticide and water by promoting **precision agriculture**. The robot will be able to spray only the areas that are affected; this reduces the pollution of the environment and conserves resources, as opposed to spraying the entire fields. In the long run, the strategy will promote sustainable agricultural farming that benefits the soil and saves the farmers on expenses.

The **scope of this project** extends beyond just technical development. It lays stress on **farmer-friendly** concepts, usefulness, faith and local flexibility. Technically, AGRIBOT is a system that unites computer vision (disease detection using CNNs), robotics (motion and task control), and natural language processing (Speech recognition and synthesis) into one, coherent system. At the social level, it is inclusive as it looks into the language variety, cultural tolerance, and farmers everyday requirements.

Agricultural robots are becoming a trend across the world. One such example is **Ecorobotix** [20], which uses AI to detect and kill weeds without destroying other plants. **Agrobot** [21], which is automated strawberry harvesting; and the **See and Spray** of Blue River Technology [22], which was developed by John Deere using machine vision to precisely spray herbicides on weeds. In the same way, AGRIBOT is in line with these developments but it is oriented to affordability, localization and human robot interaction within the Bangladeshi environment.



Fig 1: Ecorobix Robot [20]



Fig 2: Agrobot Robot [21]



Fig 3: See and Spray [22]

In the long term, the AGRIBOT framework can be expanded to include **cloud-based data storage**, **IoT integration**, and **solar-powered operation** for enhanced autonomy. The project sets the foundation for future agricultural robots that are not only intelligent but also approachable, culturally aware, and truly beneficial to farmers at every level.

1.4 Objectives

The **AGRIBOT** aims to meet the needs of farmers by automation, artificial intelligence, and multilingual communication technologies to detect and manage the disease of plants at an early stage. The proposed project is dedicated to the combination of robotics, computer vision and human-robot interaction in order to make agriculture more productive and sustainable. These

objectives are subdivided into **primary research objectives** and **secondary developmental objectives** as below.

Primary Objectives:

1. To develop a **multilingual voice interaction system** that would allow farmers to speak with the robot in the natural way, using both Bangla and English languages.
2. To come up with a **CNN-based leaf disease detection system** that can detect various types of crop diseases with a high level of accuracy.
3. To incorporate AI modules to a robotic platform (**motors, sensors, and actuators**) in order to carry out agricultural activities automatically.
4. To analyze the performance of the robot using **surveys, interviews and field tests** of the farmer.

Secondary Objectives:

1. To create a **low-cost, scalable hardware design** suitable for smallholder farmers.
2. To examine the preferences of farmers in **the appearance, role and personality** of agricultural robots.
3. To add to the **research literature on smart agriculture**, namely, in the field of multilingual human-robot interaction.
4. To expand opportunities in the future including the option of **cloud-based data synchronization, incorporation of IoT sensors, and solar-power operation**.

1.5 Researchable Questions

In order to attain the above objectives, this study is aimed at answering the following critical questions:

1. What are the effective ways to apply **Convolutional Neural Networks** to detect various mango leaf diseases accurately in various real-life environments?

2. Which is the most effective **hardware-software integration** approach to the implementation of automated detection and spraying with the use of low-cost hardware like Raspberry Pi and Arduino?
3. What is the role of **IoT incorporation** and **Bengali voice recognition** in improving the access, scalability, and useability of agricultural automation systems by the local farmers?
4. How efficient is the proposed system in **managing diseases** as compared to the traditional manual inspection systems?
5. How is it possible to **generalize** or **extend** this integrated framework in other crops, diseases, or environmental settings at a low cost and easy to use?

These research questions will inform the design, development, and testing of the system, and make sure that the system does not only meet technical excellence but also that it meets the social and practical issues of agricultural modernization.

1.6 Proposed Solution

In order to overcome the shortcomings of the traditional inspection systems and the issues that have been noted in the existing automated systems, this study has suggested a novel **Convolutional Neural Network (CNN)-based mango leaf disease detection and management model** that involves the combination of deep-learning, Internet of Things (IoT) connectivity and user-friendly automation.

Following the principle, the framework uses a **specialized CNN framework** that is prepared using a multifaceted sample of healthy and sick mango leaf photos. The model is automatic and can classify diseases like anthracnose, bacterial canker and powdery mildew with high precision even when there is an aberration in the field conditions.

In order to transform digital inference into actionable information, CNN module is incorporated with **an IoT-enabled hardware system**. Raspberry Pi 4 acts as a central processing unit, and it is fed with real-time images of a camera module attached to a mobile robotic platform. When a diseased leaf is detected, the processor triggers an **automated spraying mechanism** controlled through Arduino-based actuation circuits.

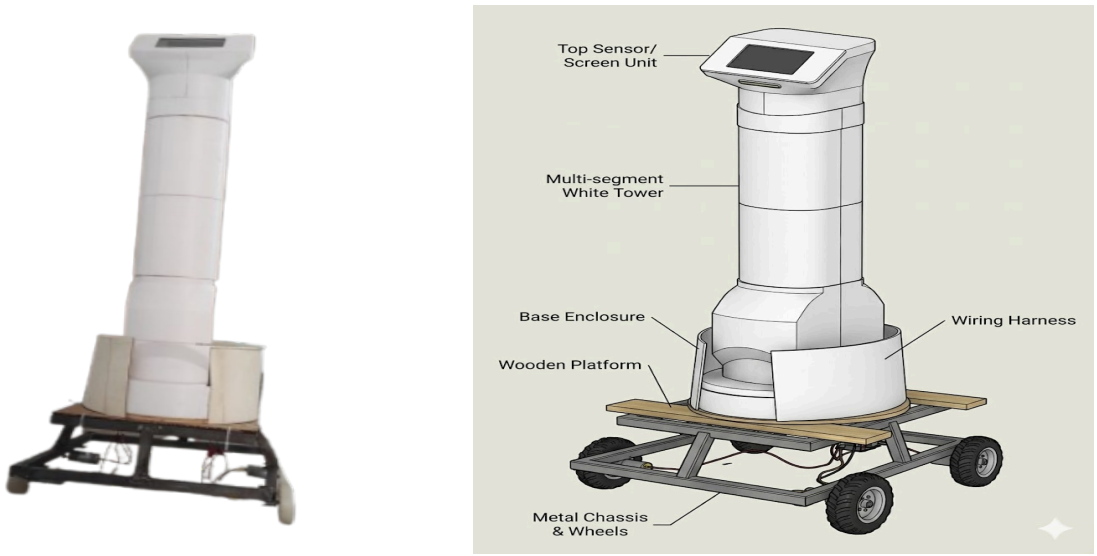

Fig 4: Structure of Agribot

Simultaneously, the solution will happen to include a **Bengali voice-interaction interface** that will allow the farmers to use the system and provide verbal feedback in their mother tongue. The introduction of speech recognition and voice output bridges the divide between high tech and non-technical people and allows accessibility to the smallholder farmers with limited literacy or computer skills. This human-robot communication layer makes the system harmonize technology innovation with the usability in the socio-cultural context.

In contrast to the earlier researchers that considered only the detection accuracy, the framework proposed highlights the **end-to-end automation**, or visual diagnosis to the mechanical response and communication to the user. The approach aims to:

1. Provide **field-ready performance** with real-time image processing and dynamic model training.
2. Be **cost-efficient** with commercial microcontrollers and sensors
3. Support **scalability** for future expansion to other crops or disease types via dataset retraining.

In general, the solution proposed is a continuation of the smart agriculture frontier because it integrates the **AI-driven analytics** with the **IoT automation** and the **human-centered interaction** into the singular platform. It presents a feasible solution to sustainable, precision-based farm-related activities in third world countries, like Bangladesh.

CHAPTER 02

Literature review

2.1 Agricultural Robots

Agricultural robots are not a new concept, as their development started in the middle of the 20th century, which was also the period when the wave of mechanization of agriculture took place during the Green Revolution. The main efforts were made early by mechanical automation; tractor mounted harvesters, tractor mounted threshers and irrigation systems. These systems also had great savings of manual labor, but they were still **mechanically deterministic**; that is, they were not adaptable and intelligent.

Towards the end of the 20th century, **sensors, microcontrollers, and computer vision** started to infiltrate agriculture. The robots were now able to sense their surroundings as opposed to carrying out preprogrammed functions. An example of this is the **Harvey robot** (invented in the 1980s), which was able to harvest cucumbers autonomously in greenhouse environments, which was one of the earliest successful agricultural robots.

2.1.1 Modern Agricultural Robots

There are the following types of modern agricultural robots:

1. **Harvesting Robots**: Robots like those that pick strawberries in Japan or tomato picking robots in the Netherlands. These robots make use of computer vision to detect the ripe fruits and robot arms to collect them without destroying crops.

2. **Weeding Robots**: Robots such as **Ecorobotix** in Switzerland identify weeds and crops and spray them with treatment using AI to cut back on the amount of chemicals used by up to 90%.

3. **Seeding and Planting Robots**: Autonomous seeders map fields and plant seeds with millimeter accuracy.

4. **Monitoring Robots**: Drone-based systems capture aerial images to detect crop health and stress patterns.

5. **Multipurpose Robots**: Integrated platforms, often called **farmbots**, that can perform multiple tasks, including weeding, watering, and disease monitoring.

Name	Category	Company Name	Objective	Limitation	Reference
Agrobot E-Series	Harvesting Robot	Agrobot	Gently picks Strawberry without damaging	Slow on uneven fields, limited to strawberry	[21]
Naïo Oz	Weeding and Soil Monitoring Robot	Naïo Technologies	Reduces use of chemicals,improves soil healths	Useful only in small firms, needs daily maintenance	[23]
See and Spray	Precision Spraying Robot	Blue River Technology	Uses AI to spray only weeds, reduces chemical use up to 90%	Performance drops in poor lights,high setup cost	[22]
Ecorobotix ARA	Weeding Robot	Ecorobotix	Runs on Solar power, reduces chemical use	Slow movement, cannot work well in cloudy weather	[20]
Robotti	Multipurpose Robot	Agrointelli	It can seed, spray and weed, it works on different crops	It needs accurate GPS Mapping, High Maintenance cost	[24]

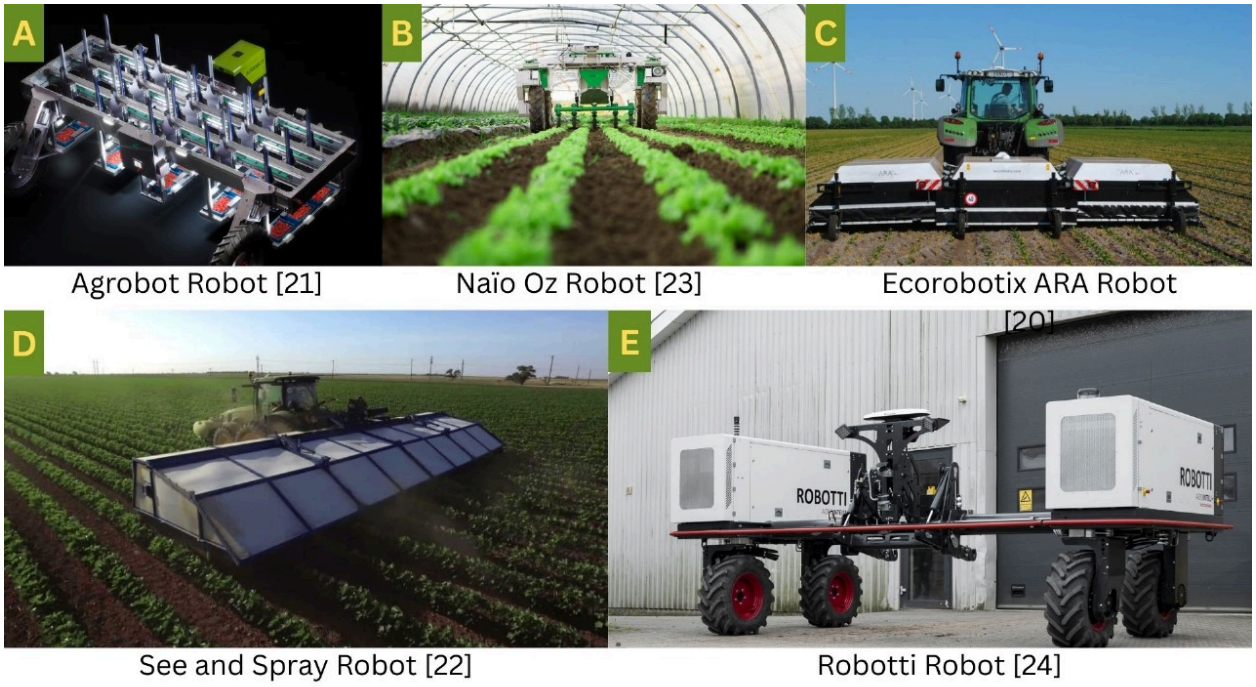

Fig 5: Agricultural Robots

Many types of agricultural robots have been developed to support precision farming and reduce human labor. These robots mainly fall into two categories:

1. **Self-propelled robots**

These robots vary widely in size and purpose. Traditional farming machines—like tractors, sprayers, and combine harvesters—have become semi-autonomous using GPS/GNSS auto-guidance. These machines can drive along field rows on their own, turn at the headlands, and coordinate tasks such as unloading, while still being monitored by a human operator. Newer autonomous, cabinless tractor robots have also been introduced. They work with standard farming tools and are designed for high-power, large-scale tasks such as ploughing, seeding, fertilizing, spraying, and harvesting.[98]

Smaller self-propelled robots have also been developed for low-power jobs like scouting and weeding. Most are research prototypes, but some commercial examples exist, such as robots for seeding and nursery container handling. Small robots like Xaver are intended to work in teams, representing a shift from using large heavy machinery to multiple small lightweight robots to reduce soil compaction.



Fig 6: Self-propelled robots [98, 100, 101]

2. Robotic smart implements

These tools carried by a tractor or vehicle are also being developed and used. Some are already commercial, such as robotic systems for transplanting, lettuce thinning, and mechanical weeding. Others are still in development for tasks like fruit harvesting, vine pruning, and orchard operations such as flower and fruit thinning.[98]



Fig 7: Robotic Smart Implements [98, 102,103]

2.1.2 Limitations

Most industrial farming robots are geared towards industry level farming in the developed countries, even with their advancements. Smallholder farmers in developing countries cannot afford them because they are usually expensive. Moreover, a number of the robots presuppose a high level of literacy and technical skills in users and do not put into consideration socio-cultural backgrounds where literacy rates are low.

2.1.3 Relevance to AGRIBOT

AGRIBOT will reach these drawbacks by incorporating low-cost hardware (Raspberry Pi and Arduino) to maintain its affordability and accessibility to farmers. It also has voice interaction in both Bangla and English that simplifies language constraints and allows users to use the system with ease. Moreover, AGRIBOT is also designed to offer several farm functions, such as disease identification and controlled navigation, and therefore, it can be regarded as a highly flexible and multi-purpose solution to the current challenges in agriculture.

2.2 Disease Detection

Plant diseases are a significant threat to world agriculture and the production of mango (Mangifera indica L.) is particularly susceptible since foliar diseases may quickly diminish the yield as well as the quality of the fruits. The conventional way of identifying the diseases depends on the visual inspection of the leaves by the farmers, which is slow, subjective, and unequal, as well as requires professional expertise. Consequently, numerous new researches have investigated AI-related solutions to automatize and enhance disease detecting. As seen in review papers by Ahmad et al. [25] and Wani et al. [9], a significant proportion of the current literature only covers classification, but much fewer recommendations suggest a treatment or realistic deployment strategy. Li et al. [3] and Nagaraju and Chawla [10] also point out good development in the accuracy of deep learning but also indicate that there are still challenges in the application of deep learning in practice. In the meantime, Elbasi et al. [26] mention that disease detection is a subset of the wider agricultural transformation, where AI aids in the irrigation control and monitor the fields with robots among other tasks. Taken together, these studies demonstrate a direction towards more holistic, practical, field-ready systems which are a combination of AI models, sensing technologies, and smart hardware.

2.2.1 Evolution of AI and Deep Learning Models

The central part of any automated system of disease detection is the classification model, which is an algorithm that has been trained to tell the difference between a healthy leaf and a diseased leaf. The discipline has over time developed to a level of traditional machine-learning to sophisticated deep-learning models.

2.2.1.1 Dominance of CNNs in Plant Disease Classification

Convolutional Neural Networks (CNNs) are currently the most popular models of running image-based agricultural diagnosis since they automatically learn features based on the raw image. Numerous investigations managed to use CNNs on mango leaf disease detection [27, 28].

1. **Lightweight and Hardware-Friendly Models**

Stronger models were primarily tested in the early studies to demonstrate efficacy. Nevertheless, mobile phones or weak power devices are common to farmers, and, therefore, recent efforts focus on lightweight architecture.

A good example is LeafNet, which identifies seven significant mango leaf infections with 98.55% accuracy along with only 3.25 million parameters [29, 8].

Equally, MobileNet-based networks, such as Optimal MobileNet (OMCNN) [30] and MobileNetV2 [31], demonstrate that small models do not necessarily require significant performance.

2. **Advanced and Hybrid Architectures**

Simultaneously, researchers are still enhancing accuracy of classification by using more advanced and sophisticated models. ConvNeXt, a product of architectural based principles of Vision Transformers, was able to distinguish between pathogens and pest-induced damage on mango leaves with an accuracy of 100% [32]. ViTs and their optimized counterparts, like DeiT, have also shown good performance, with the highest accuracy of up to 99.75% [33]. Hybrid models including CNN-GRU integrations [34], Enforced Stack Deep Neural Networks (ESDNN) [5], and CNN models with feature reduction methods [35] improve performance by using the synergistic benefits of architectures.

3. **Transfer Learning to Handle Limited Datasets**

One of the biggest issues of agricultural AI is the lack of large and diverse datasets of images. Transfer learning facilitates to address this drawback through the use of models that have been trained on large generic datasets and focused on crop-specific images. InceptionV3 with data augmentation has reached 99.87% accuracy using the approach [36]. DenseNet121 [37], ResNet50 [38], and other more specific models [12] are also ranked as top transfer-learning models by all means.

4. **Traditional ML and Hybrid Approaches**

Although the use of deep learning is dominant in the field, simpler or hybrid techniques are still useful, especially in a situation where interpretability or limited data is a major issue. Hybrid models using CNNs together with other classical classifiers e.g. CNN-SVM hybrids [39] and CNN-KNN hybrids [40] have been demonstrated to have high performance in restricted environments. Neural networks that are combined with SVMs are also offered as an ensemble approach which offers strong alternatives [41], as are feature-based methods such as decision trees [43] which will still provide viable alternatives when computational efficiency is a requirement. Consequently, such practices continue to exist in specialized uses even in the context of the wider move to deep learning [42].

2.2.1.2 Image Processing and Sensing Technologies

It is up to the images that AI models absorb that defines their goodness. Images of real-life orchards have the disadvantage of being poorly lit, with a cluttered background, and motion blur. This has given rise to a similar line of research on methods of improving raw images and investigating novel forms of sensors.

1. **Preprocessing and Feature Enhancement**

A number of reviews have highlighted the importance of image preprocessing in enhancing the classification performance [13, 14]. Typical methods are techniques of segmentation by using deep learning [44] or traditional methods like K-means with GLCM features [45] to extract the leaves against complicated backgrounds. Other contrast enhancement techniques such as BBHE are also commonly used to outline diseased areas to be detected more accurately [46]. Also, there are studies that examine feature-specific analysis, where localized disease spots are studied [47] or structural leaf properties such as vein patterns [48]. These preprocessing plans

have been proven to work with numerous crops, such as apples [49, 50] and tomatoes [51] and have also been effectively utilized in larger agricultural activities like in fruit sorting [52].

2. **Real-Time Leaf Detection for Field Robots**

A mobile robot has to identify the leaf in its camera image before categorizing a disease. YOLOv5, a fast object-detection, reached 96% accuracy in real-time mango leaf disease detection [53], so it is a good candidate to be deployed in robots.

3. **Advanced Sensing Beyond RGB Cameras**

Normal RGB cameras only realize the disease when it has visible symptoms. Researchers have resorted to more sophisticated sensors in order to detect problems at an earlier stage [54].

4. **Hyperspectral and Thermal Imaging**

Hyperspectral cameras have hundreds of wavelength bands, which detect the initial signs of stress before the human eye can. Thermal imaging is beneficial in identifying temperature variations associated with disease. Such techniques are capable of early-warning [55].

5. **Ultrasonic Sensing**

In a new study, leaf diseases of mangoes were classified with a precision of 90 percent by the application of ultrasonic signals [56]. This technique is cheap, and it is not dependent on the lighting conditions.

2.2.1.3 System Integration and Real-World Deployment

The number of models that work very well in the laboratory is huge; however, in the real world, things are different. Orchards have varying leaves in terms of their orientation, light, weather, and visible light. This is one of the largest gaps that still persists, the so-called lab-to-field gap.

1. **IoT-Based Monitoring Systems**

There are also numerous researchers suggesting low-cost IoT-based systems that can be used to monitor agricultural lands continuously. Some of them report the adoption of deep learning models with IoT systems to facilitate real-time disease diagnosis [57, 58]. Microcontrollers and mini computers commonly used in these applications are Arduino and NodeMCU board [60], Raspberry Pi devices [61] and ESP32-CAM boards [62] which enable easy image capture and data transfer. Others also combine CNN-based diagnosis with automated irrigation control

systems [63], and more extensive IoT systems have been used to monitor (large) orchards [64] and to measure fruit quality post-harvest [6].

2. **Mobile Robots and Autonomous Platforms**

Whereas stationary IoT devices are limited in the coverage, mobile robots can survey complete orchards.

3. **RobHortic Field Robot**

RobHortic is the proximal sensors based disease detector, although the accuracy went down to 59.8% in the field, however, down to 66.4 in the lab - which indicates how challenging it is to apply in the real world.

4. **Improving Usability**

Field robotics have also been suggested to include voice-controlled robots so farmers without technical knowledge could use it [65].

5. **Plant Variety Identification**

There are also the varieties of mangoes that must be identified by robots. Such models as WaveVisionNet enhance the accuracy of varietal classification so that the robot can refine its logic and recommendations according to the type of the particular plant [66].

6. **Expert Systems and Broader Challenges**

There is also an interest within researchers on how to combine AI-based detection with decision-making systems to aid in field management in practice. Indicatively, expert systems based on fuzzy logic have been created to prescribe the right therapy after the disease is detected [67]. Different studies are interested in new pathogens that are not reflected in the current datasets addressing the gaps which restrict the extrapolation of current models [68]. The wider, real-world impact can be achieved further with the inclusion of the principles of precision agriculture practices [69], the adherence to the guidelines of AI best-practice, and the introduction of the risk-management approaches that would guarantee safe, large-scale application of agricultural AI technologies [71, 72].

2.2.2 Comparison of Image Processing Model

2.2.2.1 Introduction

The comparison of various image processing and classification models is necessary to comprehend its relevance in the real life agricultural settings. Despite the recent progress in plant disease detection dominated by deep learning structures, their effectiveness can be dramatically different when it comes to the size of the dataset, the complexity of the environment, and the field of application. Other models are more accurate and robust and others consider computational efficiency as a means of real-time deployment or low cost deployment. In the below section some of the prominent models utilized in plant disease detection and crop monitoring and their methodological peculiarities and practical importance are discussed.

2.2.2.2 Overview of Disease Detection Model

1. **Gated-Recurrent Convolutional Neural Network** (G-RecConNN) [59,78]

The G-RecConNN model combines convolutional and gated recurrent unit layers in order to learn the spatial and time characteristics of plant diseases. This composite design enables the model to respond to the symptoms of disease at an early stage due to the ability to identify inconspicuous patterns that change along the surfaces of leaves. Since it is said to be accurate up to 95%, it is more applicable in early diagnosis tasks where it is important to detect early visual cues.

2. **Optimal MobileNet CNN (OMNCNN)** [59,78]

OMNN is a small convolutional neural network, which is optimized by feature extraction and the optimization of the hyperparameters. Intended to be used in mobile and embedded applications, it has a good balance in the accuracy and computational efficiency. With a 98.7% accuracy in the classification of tomato leaf disease, the model shows that compact architectures can still provide the highest-quality performance, so they are the best to be used in IoT-based application or field-ready configurations.

3. **LeafNet** [51,75]

LeafNet is a specialized CNN developed for common mango leaf disease detection using the MangoLeafBD dataset. It has about 3.25 million parameters, which provides a good trade-off between the model size and detection. LeafNet has obtained results of 98.55% accuracy which

demonstrates its usefulness in crop-specialized classification problems in cases where curated datasets exist.

4. **DenseNet-121** [12,76]

DenseNet-121 is a feature-dense convolutional network that promotes feature reuse through dense connectivity between layers. Despite its general image recognition work being widely successful, it may perform differently on agricultural datasets and its performance is dependent on the diversity of the datasets and the complexity of the diseases-class. It got an accuracy of 90.81% on 38 types of crop diseases which indicates its ability to conduct multi-class analysis of agriculture.

5. **ResNet-50 and VGG16** [12,74]

ResNet-50 and VGG16 are defined as transfer learning models that have deep hierarchical architectures. The models are common in agricultural processes, with the dataset evaluation, baseline comparison, and variational analysis, instead of being task-specifically optimized. They are very robust and hence useful in benchmarking new datasets or comparing different architectures.

6. **RobHortic Spectral Imaging Field Robot** [8]

It is a spectral imaging system that works together with robotics to detect asymptomatic pathogens on carrot crops. Spectral imaging, unlike the usual RGB-based CNN [77] algorithms, depicts minor physiological variations that cannot be seen by the human eye. The model was 66.4% and 59.8% accurate in laboratory and the field respectively which aims at depicting the difficulties of environmental variability in real-life context despite the highly developed sensing technology.

7. **Generic CNN Models** [73], [50], [30]

Generic CNNs continue to be popular in automated crop disease detection but are prone to constraints in situations of high variability in real-world applications. Their performance varies with the background noise, lighting variations and lack of complete training data. These models still give some background and base points on which more specific architectures can be built.

2.2.2.2 Comparison Table of Disease Detection Model

Model	Appliance	Accuracy	Reference
Gated-Recurrent Convolutional Neural Network (G-RecConNN)	Early diagnosis of plant diseases	95%	[59,78]
Optimal MobileNet CNN (OMNCNN)	Tomato leaf disease classification with feature extraction and hyperparameter optimization	98.7%	[59,78]
LeafNet	Common mango leaf disease detection using MangoleafBD dataset of 3.25 Million Parameters	98.55%	[51,75]
DenseNet-121	Classification into 38 instructions for disease detection	90.81%	[12,74]
RobHortic Spectral Imaging Field Robot	Detection of asymptomatic pathogens in carrots	66.4% (lab), 59.8%	[8]

CHAPTER 03

Requirement Engineering

3.1 Survey Design

In order to design the AGRIBOT in a user-centered manner, AGRIBOT structured surveys and semi-structured interviews were held with local farmers. It was aimed to learn about their perception, expectation and usability issues of agricultural robots. The survey was concerned with the appearance of the robots, the choice of the most appropriate ways of interacting, perceived usefulness, and financial feasibility. These insights led to a match between AGRIBOT development, the needs and real-world requirements of Bangladeshi farmers, which guaranteed their acceptance and sustainability.

3.2 Objectives of Survey

The primary goals of the survey were to gather the opinions of users which would provide a first hand contribution to the design and functionality of AGRIBOT. In particular, the survey was supposed to:

1. **Identify preferred interaction modes:** Ascertain how the farmers want to interact with the robot, via Bangla voice commands, touchscreen, or mobile application.
2. **Gather expectations for AGRIBOT's tasks:** Learn what farming activities (e.g., disease detection, spraying, watering, data reporting) will be the most appreciated among farmers.
3. **Determine acceptable price range:** Establish the economic viability through establishing a reasonable price that fits within the economic ability of farmers.
4. **Explore cultural and psychological factors affecting adoption:** Research how beliefs, technology experience and usefulness perceptions of farmers influence their readiness to adopt AGRIBOT in their farming practice.

3.3 Survey Technique

The questionnaire was to be user-friendly, reliable, and inclusive to people living in the rural areas.

1. **Sample Size: 50 farmers** were sampled and the sample was appropriately representative due to their age, education, and experience of farming.
2. **Regions Covered:** Survey activities were done in the area of **Rajshahi, Gazipur** and **Feni** regions that had varying climatic and agricultural environments.
3. **Data Collection Tools:** A blend of **questionnaires** and **interviews (face-to-face)** was applied. Structured responses were obtained through questionnaires, whereas in interviews, it was possible to get a more profound understanding of the attitudes of farmers and challenges confronting them.
4. **Language:** The questionnaire was to be done in **Bangla** so that it was easy to understand and comprehend by the respondents who may have different levels of literacy.
5. **Survey Duration:** Each staff session took about 20-30 minutes, based on the interest of the participants.
6. **Assistance Provided:** In case of the illiterate farmers, the facilitators read questions and their answers were accurately recorded.

3.4 Survey Results

The survey has provided a good understanding of the preferences of the farmers in terms of the modes of interaction, the nature of features they want, the design expectations and the cost-effectiveness of the AGRIBOT. The findings offered a feasible basis of the optimization of the usefulness and adoption of the robot in farming practice.

3.4.1 Interaction Preference

Farmers were very enticed to use simpler and intuitive forms of communication that would need little technical expertise.

1. **Bangla Voice Commands – 90% Support:**
   A vast percentage of the respondents preferred the Bangla voice-based interaction citing ease of use and ease of access to such interaction by the respondents who had limited

literacy or technical expertise. The farmers also noted that they would find it easier to use familiar spoken commands on AGRIBOT, which would render the device less threatening to use.

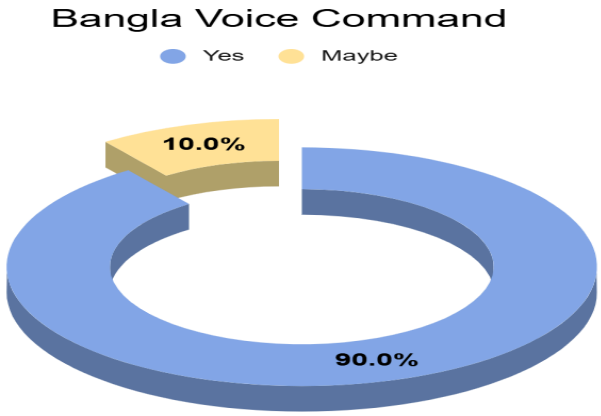

Fig 8 : Bangla Voice Command Survey Graph

2. **English Support – 20% (Younger Farmers):**
   A lesser percentage of young, more technology friendly farmers were interested in communicating in English, with the sole reason being to be in line with the emerging technologies and future-proof interfaces.

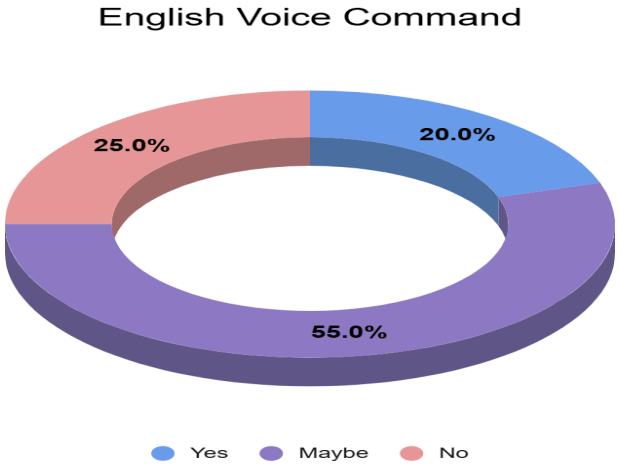

Fig 9 : English Voice Command Survey Graph

3. **Text/GUIs – 15% (Educated Farmers):**
   Farmers whose education was higher in degree expressed moderate interest in text-based or graphical user interface controls especially when used through mobile application or tablet. Nonetheless, voice-based interaction was still preferred over other methods because it is convenient and inclusive.

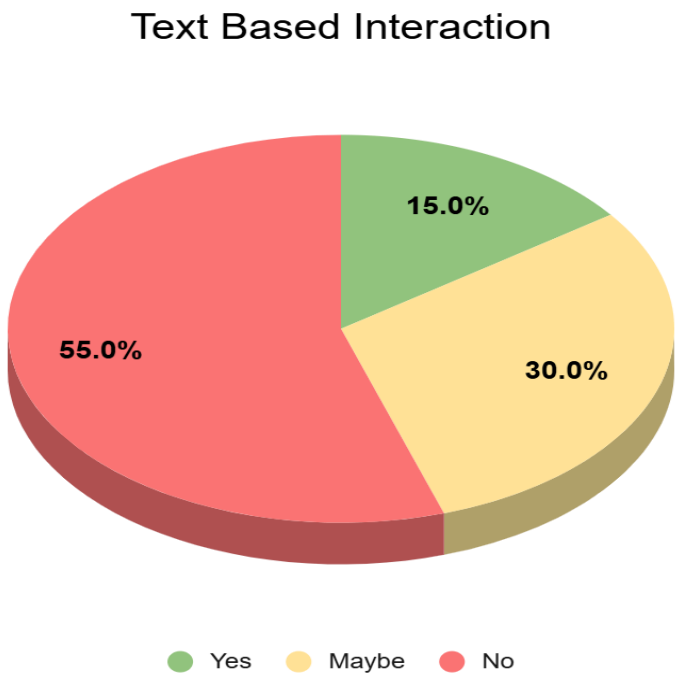

Fig 10 : Text Based Interaction Survey Graph

3.4.2 Desired Functions

The farmers were requested to determine the most beneficial AGRIBOT capabilities to their farming practices. The table below summarizes the results.

Function	Percentage of Farmers
Disease Detection	80%
Irrigation	55%

Pesticide Spraying	65%
Soil Moisture Testing	40%
Weather Alerts	35%

Disease detection (80%), as the form of demand, was the most demanded one as it showed the urgency of early diagnosing of plant diseases to reduce losses on crops. Pesticide spraying (65%) and irrigation assistance (55%) also ranked high as these things are labor intensive and need to be timely performed. The smaller percentages on both soil moisture testing and weather alerts represent secondary yet useful areas of interest in which the AGRIBOT can be further developed in the future.

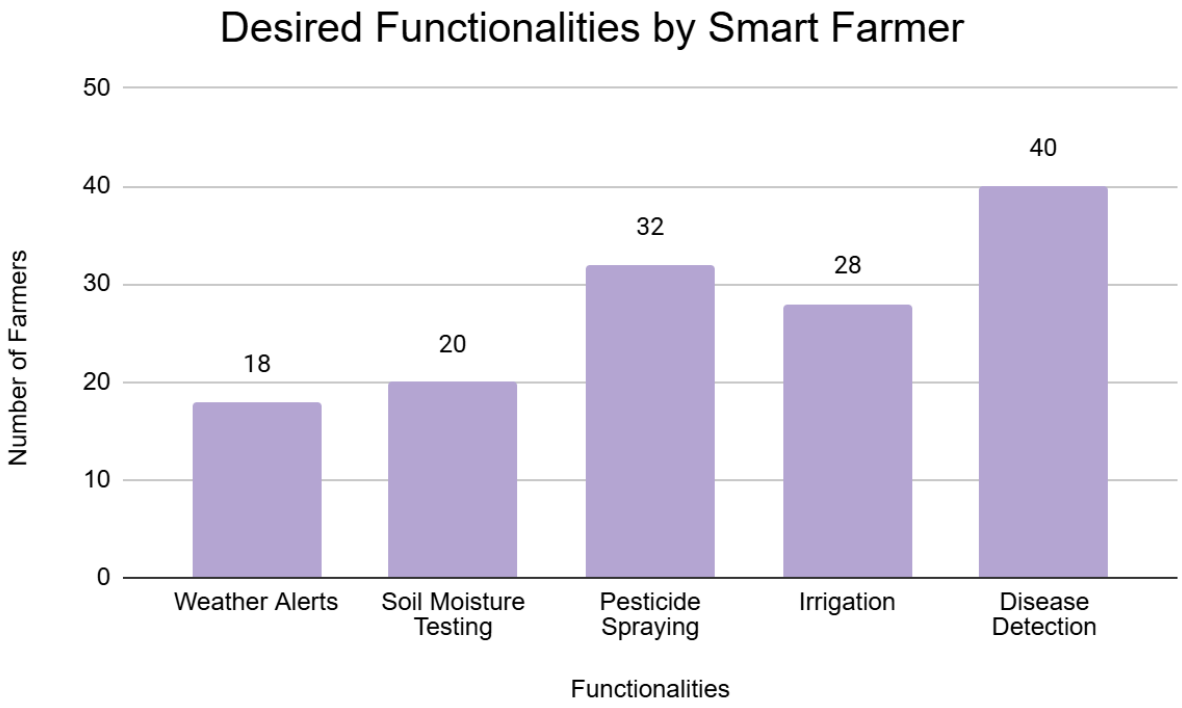

Fig 11 : Farmer Desired Functionality Survey Graph

3.4.3 Appearance Preferences

The respondents were requested to select their preferred physical design of AGRIBOT depending on the durability, usability, and familiarity.

1. **Box/Car-like Robot – 60%:**
   Most were inclined towards a compressed box-shaped or car-like appearance with the reason being that it was rugged, easy to move, and could be used in uneven or muddy areas.

2. **Humanoid Robot – 25%:**
   There were those who preferred a humanoid shape due to its perceived modernity and high-tech look, especially the younger farmers but they also expressed fears of maintenance and price.

3. **Drone-type – 15%:**
   A minor fraction favored drone-like forms to conduct aerial observation and spraying, but the vast majority of them found it less convenient to use in the field because of control challenges and increased expenses.

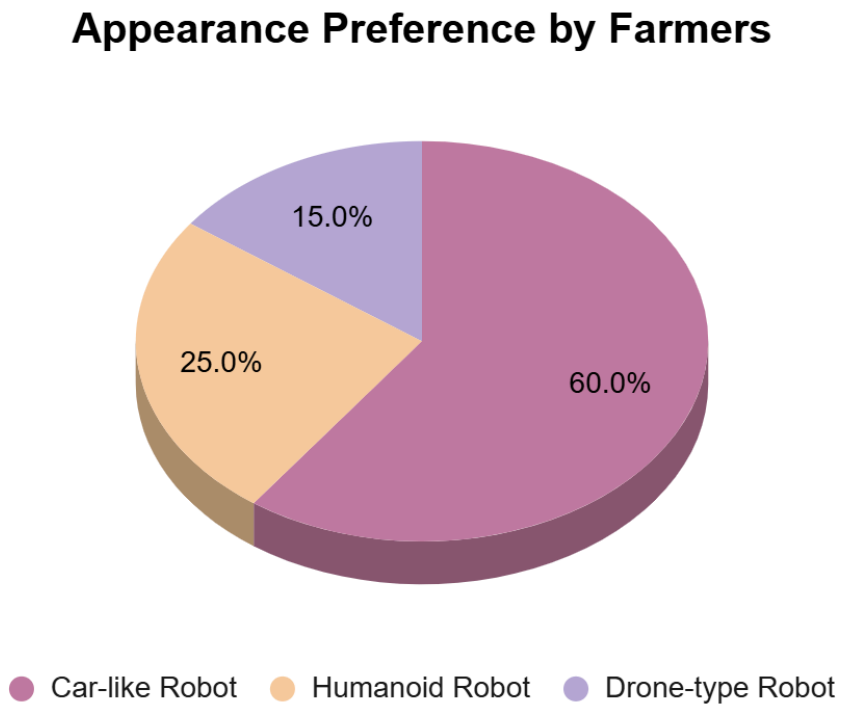

Fig 12 : Appearance Preference Survey Graph

A box-like shape was largely influenced by the fact that the farmers mainly focused on durability, stability and affordability and not on the looks of their structure. This means that there is a high value of functional reliability as opposed to fancy looks.

3.4.4 Price Sensitivity

AGRIBOT has found itself facing the challenge of affordability as a key factor that determines its adoption in the market.

1. **Acceptable Price Range:**
   The majority of respondents mentioned that their comfortable purchasing range was 10,000-15,000 BDT, which was reasonable as stated by the respondents to be used by small and medium-scale farmers.

2. **Unaffordability Threshold:**
   About 70 percent of interviewees said they could not buy a price of more than 20,000 BDT. The farmers also complained about the maintenance costs and possible repair expenses and added to the need of the cost-efficient design and the possibility of the local services.

According to the results of the survey, the essential aspects of AGRIBOT acceptance by farmers include cost, ease, and reliability. These insights will be used during the prototype development phase, thus making the system not only technologically viable but also cost-effective to the rural agricultural community.

3.5 Cultural Considerations

AGRIBOT was designed and modeled to interact with rural Bangladesh cultural setting. To make human-robot interaction work smoothly, farmers underscored on the need to respect, be simple, and adopt local language.

1. **Respectful Tone of Robot Speech:**
   The farmers wanted the robot to talk politely in a humble fashion that used the culturally relevant expressions. This goes with rural communication ethics of Bangladesh where politeness and respect is of great essence in socialization.

2. **Use of Honorifics in Bangla:**
   Participants specifically requested the use of local linguistic honorifics such as “আপনি” (Apni) instead of “তুমি” (Tumi), as it conveys respect. The inclusion of such speech nuances was seen as essential to making the robot appear more “familiar” and trustworthy rather than mechanical or foreign.

3. **Avoidance of Overly Complex Interfaces:**
   Since farmers have different levels of literacy, it is advised that the visual and interactive aspect of AGRIBOT should be kept minimum and easy to understand. Text-laden and technical interfaces were avoided in favor of icons and simple Bangla phrases and voice guidance.

These cultural factors underscore the importance of localization both in terms of language as well as behavior which makes sure that AGRIBOT is considered as a culturally integrated help and not an imported technology.

3.6 Psychological Aspects

Another significant psychological factor from the survey that influences the acceptance and long-term participation of farmers with AGRIBOT was also identified.

1. **Perception of Reliability:**
   The farmers saw robots as a potentially reliable tool that would help lower their physical efforts and provide stability in the routine agricultural activities. This perception was however subject to the stability and repairability of the robot as shown.
2. **Fear of Technical Breakdowns:**
   Another issue that was identified by the participants was the risk of technical failures. Most people were unsure on what they would do in case the robot failed to work meaning that it required after sales services and training of local technicians.
3. **Trust and Endorsement by Local Authorities:**
   Farmers have noted that their readiness to use AGRIBOT would rise a lot when such farming extension officers, local representatives of the Union Parishad or trusted cooperatives adopt, apply and recommend the usage of AGRIBOT. This underscores the importance of the community trust networks in speeding up the adoption of technology.

Technical performance alone is just as important as psychological comfort and trust. The creation of user confidence by demonstrating the product via community, ensuring reliability and continuous support will be crucial to the success of AGRIBOT in the rural areas.

3.7 Analysis and Implications

The aggregated results of the cultural, psychological, and technical approach give the definite design trends toward further development of AGRIBOT.

1. **Voice-First Design is Essential:**
   Since the user inclination towards the Bangla voice interaction is very high (90%), AGRIBOT should focus on voice-activated interfaces that run on the automatic speech recognition (ASR) and natural language processing (NLP). Literate users can have text or GUI options as secondary input modes.
2. **Box-like Design is Most Acceptable:**
   The box-shaped design, which is supported by 60% of the respondents, is both simple in functional purposes, durable and costs less, and it suits the rough agricultural environments. This design alternative also fits into the cultural anticipations of usefulness, purpose-based tools.
3. **Affordability as a Core Design Principle:**
   The price sensitivity analysis validates the fact that AGRIBOT should not exceed 15,000 BDT to be adopted by large scale. Material choice, optimization of hardware and planning of production should be guided by this affordability level.
4. **Community Integration and Training:**
   This will be long term because it will rely on the training of local technicians and awareness programs. The ability to empower the farming community to operate and maintain AGRIBOT will be beneficial in terms of the adoption rate and the reluctance to maintain the machine.

The integration of cultural respect, affordability, and voice-based usability positions AGRIBOT as a **socially adaptive and user-centered agricultural assistant**. These anthropocentric understandings will close the gap between sophisticated robotics and the real-world agricultural requirements so that the technology can be beneficial to the economic and the cultural aspects of rural Bangladesh.

CHAPTER 04

Methodology

4.1 System Design

The proposed AGRIBOT mango leaf disease detection system wireless network architecture will combine imaging, communication and automation technologies to allow efficient, autonomous diagnosis of foliar diseases. The system is launched by a camera module that captures images of high resolution and quality of mango leaves continuously which is the key input in detecting the potential infection. Such images have been moved to a microcontroller unit (MCU), where they are processed in advance compressing, filtering, and structuring data to be transmitted. The processed data is then directed to a central server by use of a wireless access point which will provide a smooth and reliable flow of information between the field unit and the data center.

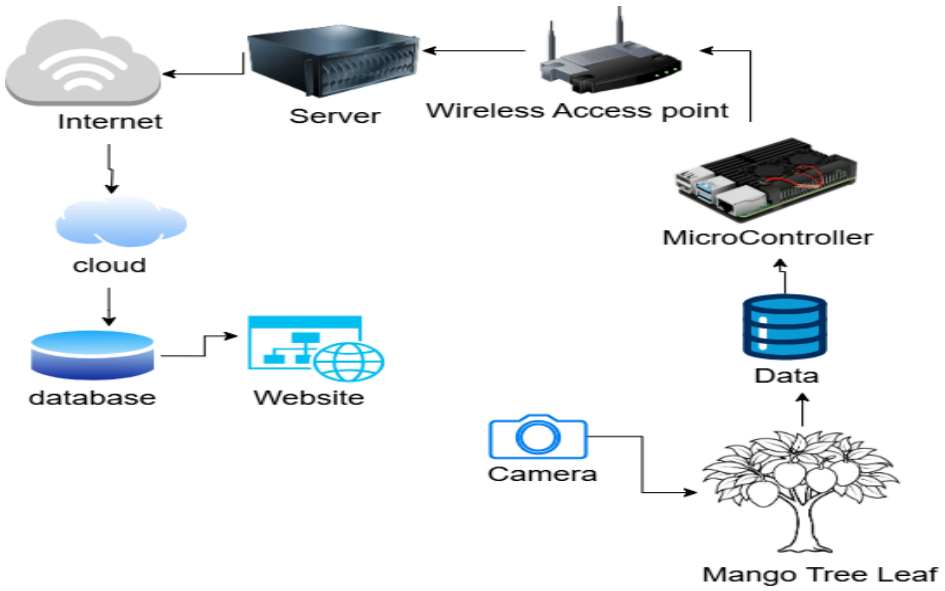

Fig 13: System Architecture of Agribot

The received data is analyzed on the server side and detected as an image and disease with the help of the developed CNN-based image processing algorithms. These algorithms detect early disease indicators in the form of anthracnose, bacterial canker and powdery mildew through color change, texture and pattern of lesions on the leaves. The obtained data is then

stored in the cloud storage which enables scalability, data security and remote availability. A structured database is stored within the cloud infrastructure to have vital records in an orderly manner that are easily retrieved. This information can be accessed by farmers, researchers, and agriculture professionals via a web-based dashboard, and they will have real-time access to the general health of mango trees. This connection between data gathering, cloud computing and wireless networking creates a sound and trustworthy disease management tool that can function under partial human intervention.

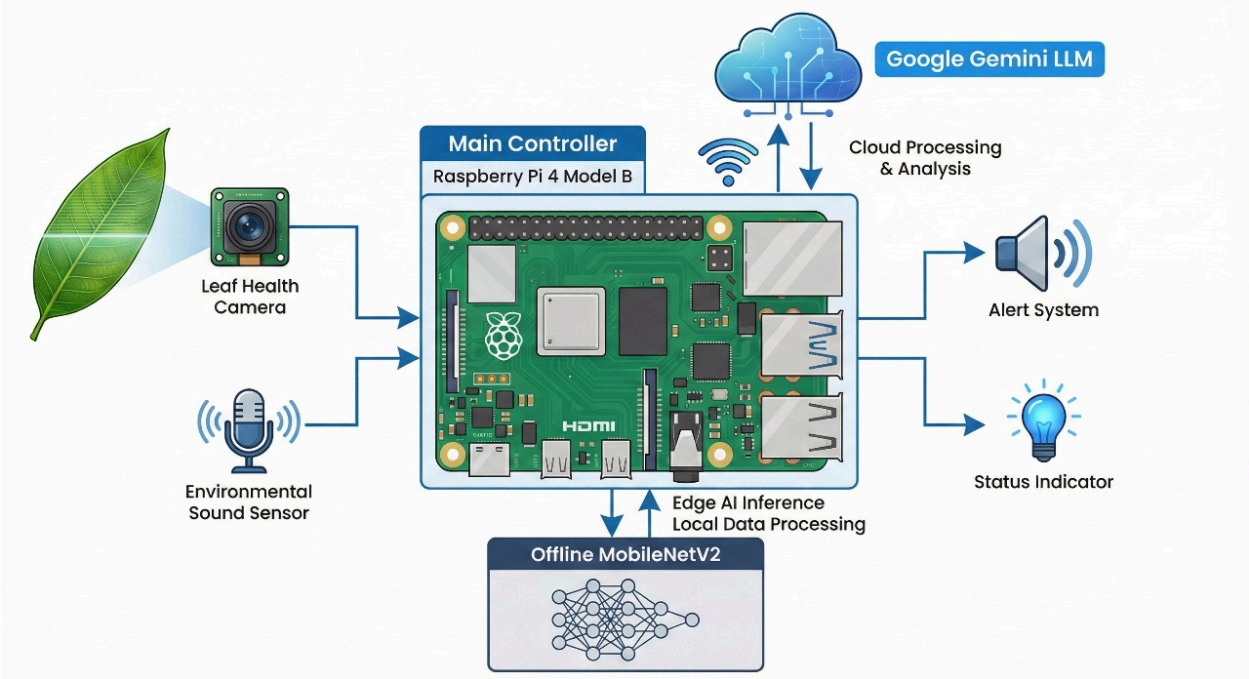

Fig 14: Infographic System Diagram of Agribot

The general system architecture of AGRIBOT is modular in nature, whereby the various functional units are intended to work separately, but are at the same time integrated well with the rest of the system. This modularity ensures that the scalability is improved, but also ensures that troubleshooting and upgrades in the future are improved since individual components can be upgraded and do not need to be redesigned. The major principles that will be applied in the design of AGRIBOT include affordability, accessibility, efficiency and robustness, so that the robot will be viable and useful to small- and medium-scale farmers.

The robot integrates three main subsystems:

1. **Hardware Subsystems**, including the robot body, camera, sensors, and actuators.

2. **Software Subsystems**, covering the CNN-based disease detection algorithms, speech recognition (ASR), and voice response (TTS) modules.

3. **Interaction Subsystems**, which handle user communication through voice commands and spoken feedback.

All of this makes the system a closed-loop in which the farmer provides an order, the AGRIBOT processes it, and provides the necessary task, and then reports the results in a natural and comprehensible way. The responsiveness, intelligent, and user-centered nature of the robot are by virtue of this interaction cycle.

4.1.1 Comprehensive Functionality

The **AGRIBOT** system starts with the Disease Detection process with the central processing and control unit being the Raspberry Pi 4. The Image Processing module takes the input of the onboard camera that takes images of mango leaves in the actual conditions. These pictures are preprocessed, meaning that they are improved in terms of noise, resizing, and normalization, which increases the quality of the picture and prepares it to be analyzed. After this step, the picture is divided to separate the leaf on the background so that the algorithm can concentrate on the damaged area.

Following the segmentation, the extraction of the features and statistical analysis are done to determine important texture and color characteristics that differentiate between healthy and diseased leaves. These features are extracted and then sent to a Convolutional Neural Network (CNN) to determine the type of disease and whether it is severe or not. This CNN-based classification enables the robot to identify frequent mango leaf diseases including; Anthracnose, Bacterial Canker and Powdery Mildew in real time without having to be connected to the internet.

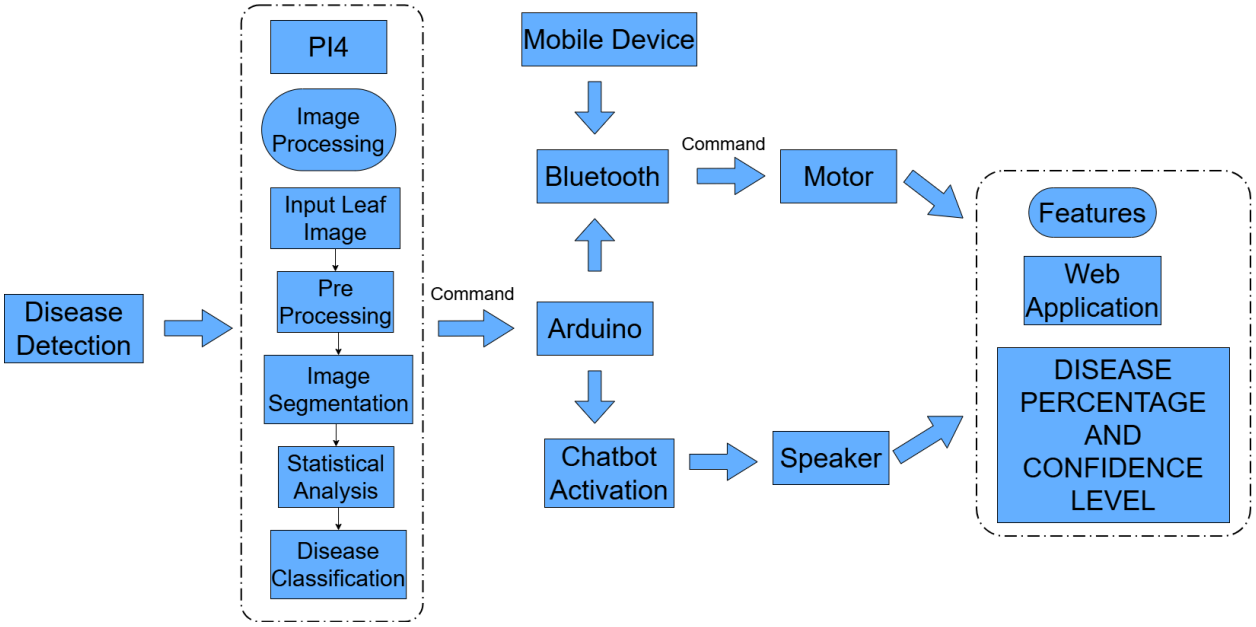

Fig 15: Block Diagram of Agribot

After the disease has been detected, the classification output is transmitted over the Raspberry Pi to an Arduino microcontroller, the communication interface between the central processing unit and the hardware peripherals. The Arduino activates different mechanical and control functions in accordance with the disease detected or the command given by the user. The Arduino and the mobile device of the farmer are connected with the help of the Bluetooth module, which allows having wireless control and monitoring in the field.

AGRIBOT functions were built based on the technical feasibility and the local farmer needs, as a result of an analysis of the field survey. All functions have been designed to solve a particular problem in the agriculture industry, and they are also user-friendly and user intuitive.

Voice Command Recognition

AGRIBOT is programmed to respond to both **Bengali** and **English** voice commands and is therefore user-friendly by farmers of all levels of literacy. The robot is able to understand spoken words using an in-built **Automatic Speech Recognition (ASR)** and respond to them. This enables the farmers to socialize with one another without using sophisticated interfaces and typing.

Disease Detection via CNN

AGRIBOT takes onboard photographs of the leaves of plants in high quality with its camera. A Convolutional Neural Network (CNN) is used to analyze these images and it is trained to detect some typical plant diseases like blight, mildew or leaf spot. The model is located on a Raspberry Pi or comparable processor, and it can run in real-time without a connection to the internet to do a diagnosis. The findings are then reported orally to the farmer, and this will be the payment between **AI prediction** and real action.

Automated Irrigation Control

AGRIBOT has a water pump system, which is a relay system that can be activated by hand or by means of an automatic mechanism. The robot is able to start irrigation when it identifies diseases associated with water stress to alleviate the problem of plant health. The irrigation can also be controlled by a simple voice command by the farmers. It is an integration that facilitates accuracy in water management that assists to conserve resources and keep the crops in ideal conditions.

Pesticide Spraying

AGRIBOT uses a servo-controlled spraying unit that enables it to spray fungicides or insecticides in case the symptoms of some diseases are identified. Data related to the detection of disease helps the robot to decide when spraying is required so that targeted chemicals are used and environmental damage is minimized. This also reduces the exposure of the hands to dangerous pesticides.

Farmer Feedback

AGRIBOT also provides either spoken feedback in Bangla or English after a task is completed, or an image of a leaf has been analyzed. This feedback makes sure that the farmers are well aware of the result of each operation. This real-time and natural system of feedback inspires confidence in the farmer and usability in general.

Data Logging

AGRIBOT has a data log, which tracks every interaction of the user, disease identification and history of operation. This data can be used in the future to compare the progress of plant health

or monitor recurrent infections. This kind of data storage enhances management of farms as well as providing the foundation of future predictive analytics and decision-support systems.

4.2 Hardware Components

AGRIBOT is developed with low cost components which can be readily acquired, thereby making it affordable and easily imitated by the small and medium scale farmers. Every component is chosen depending on its performance, cost and availability. The software and hardware systems are programmed to operate in unison where there is real-time data processing, proper disease detection, and dependable automation of farming duties.

4.2.1 Robot Hardware

AGRIBOT has a **Raspberry Pi 4 (4 GB)** as a **Central Processing Unit (CPU)** with the Raspbian Linux operating system. Raspberry Pi takes the role of running the **Convolutional Neural Network (CNN)** inference to identify leaf disease and provides the processing of **Natural Language Processing (NLP)** tasks like speech recognition and voice feedback. Its inbuilt Wi-Fi and Bluetooth system enables it to communicate wirelessly, be monitored remotely, and also have the possibilities of being integrated into the IoT.

AGRIBOT employs two micro controllers **Arduino Nano** to deal with low level and real time activities. The Arduino Nano has been specifically designed to control motors, to offer a Controlled navigation system using the bluetooth module.

The **camera module** is a Logitech C922 Pro or a Raspberry Pi Camera v2 that is used to take high-resolution images of plant leaves with a resolution of 1080p. Before the images are sent into the CNN to be classified, these images are preprocessed with the help of the OpenCV library. It allows one to detect disease accurately depending on the light and background status that occurs in actual farms.

The **audio system** of AGRIBOT incorporates a microphone to respond to voice commands of the farmer and a speaker to provide voice feedback in both **English** and **Bengali**. This arrangement facilitates two-way voice communication and farmers can speak to the robot normally without the use of screens or text-based user interfaces.

The **mobility system** comprises four geared DC motors fitted to rubber wheels that are fixed on a robust aluminum chassis. An L298N dual H-Bridge motor driver drives the motors and offers

them direction and speed control. This design gives the AGRIBOT stability and traction enabling it to navigate with ease across all forms of farmland.

In order to make sure that it is environmentally aware, AGRIBOT has a number of **sensors**, such as ultrasonic sensors that can identify obstacles, GPS module that allows it to navigate, and IMU sensor to sustain its balance and orientation. All these parts make the robot self-guided and safe within the field.

Other **actuators** fitted in AGRIBOT are a relay-controlled 12V water pump, which drives when needed to perform irrigation, and a spraying system with a servo motor to spray either pesticides or fungicides. These modules also allow the robot to automatically make corrective actions when some conditions are met such as having detected a disease.

To operate, the robot has a **12V 2200 mAh LiPo battery** with an adequate capacity to allow the robot to operate in the field. To provide a safe and efficient operation of the Raspberry Pi and other low-voltage components a **step-down converter** provides a constant 5V, which is used to power these devices.

4.2.2 Component List

Component	Quantity	Cost(USD)	Cost (BDT)	Reference
Raspberry Pi 4	1	$53.21	6500	[79]
Arduino Nano	1	$4.90	600	[80]
Camera Module	1	$20.46	2500	[81]
DC Motors	4	$9.82	1200	[82]
Motor Driver	2	3.66	440	[83]
Water pump + relay	1	$9.82	1200	[84],[85]
Battery Pack	1	$18.01	2200	[86]

Chassis Assembly	1	$20.46	2500	
Total		$140.34	BDT 17140	

4.2.3 Functional Description of Components

Raspberry Pi 4 (Main Controller):

Performs the functions of the robot brain. It executes the convolutional neural network (CNN) model to detect mango leaf disease, processes data logs, and responds to messages with other modules including the Arduino and the cloud server. It also takes speech recognition (ASR) and text to speech (TTS) functionalities to interact with the user.

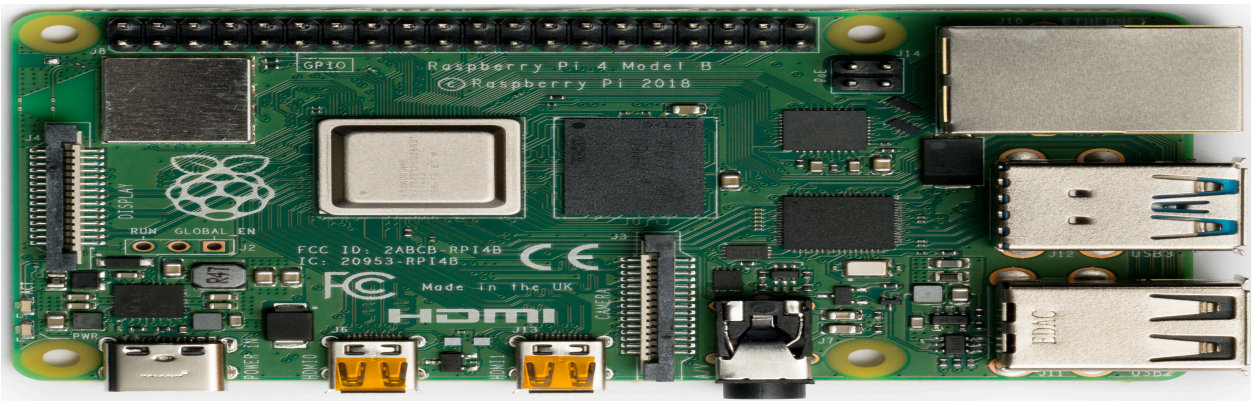

Fig 16: Image of Raspberry pi 4 [87]

Arduino (Microcontroller Unit):

In charge of the low-level control operations that are real time, including movement of motors, sensor data collection and controlled navigation. It communicates with the Raspberry Pi through serial (UART) communication to execute commands efficiently.

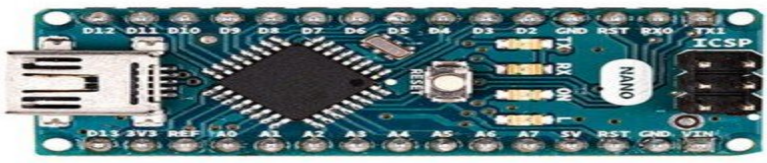

Fig 17: Image of Arduino Nano [88]

Camera Module

Takes high resolution pictures of mango leaves to detect disease. The gimbal has a camera that can be moved in various angles and heights to capture images very well.



Fig 18: Image of Camera Module [89]

DC Motor

To operate and run the wheel of Agribot, DC motors are used because of its ease of speed control and high starting torque.



Fig 19: Image of DC Motor [90]

Motor Driver

Takes Low power from the Microcontroller(Arduino Nano) and Converts it into High power to control the speed, direction and torque of the motor.

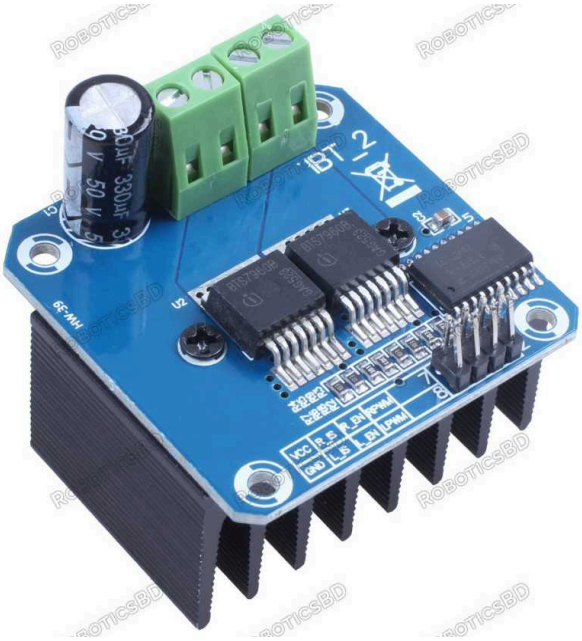

Fig 20: Image of Motor Driver [83]

Pump and Sprayer Unit:

Operated through a relay module controlled by the Arduino. It sprays or irrigates locally when a disease has been identified or at the command of farmers.



Fig 21: Image of Pump and Spray Unit [84]

Battery Pack:

Supplies power to both the Raspberry Pi and Arduino subsystems. The battery pack has a voltage regulator circuit so that there is constant power supply and overcurrent safety.



Fig 22: Image of Battery Pack [86]

Chassis and Motor Assembly:

All mechanical and electronic components are supported on the chassis. Mobility is provided by four DC-motors (two per side) which are driven through an L298N motor driver to allow movement in the forward and backward directions and left and right directions.

4.2.4 Circuit Diagram

AGRIBOT hardware architecture will be a combination of various electronic parts to allow accomplishing image acquisition, wireless communication, motor control, and speech-based interaction. The main components are a Raspberry Pi 4, Arduino Nano, L298N DC motor driver, HC-05 Bluetooth, camera and microphone modules, Bluetooth speaker, and Li-Po batteries to use as a source of power. The coordinated work of the robot is provided by the interconnection between these components to provide real-time detection of mango leaf disease and communication with the user.

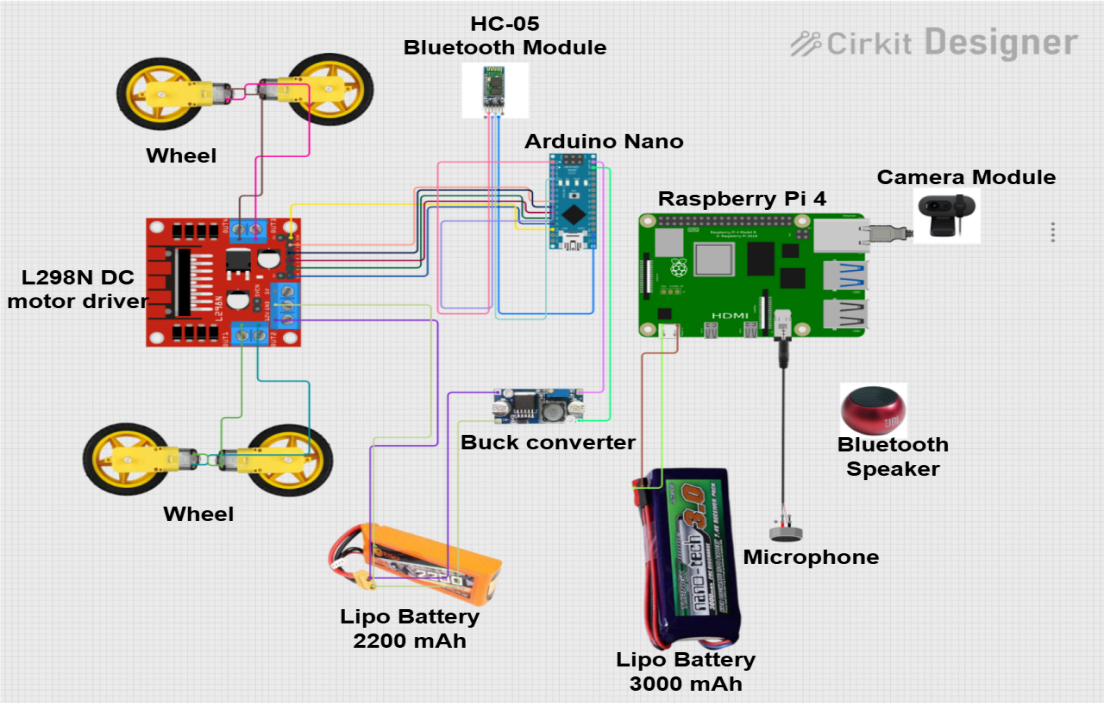

Fig 23: Circuit Diagram of Agribot

The central device of the system is Raspberry Pi 4, which is the central processing unit. It is used to process computationally intensive tasks like image processing, disease, and voice recognition. The camera module and the CSI port are linked to the Pi and images of mango leaves are taken every second and analyzed with the help of a Convolutional Neural Network (CNN) model to detect the symptoms of a disease. The Pi 4 also supports interaction with the user by using the microphone and Bluetooth speaker which allows two-way audio communication with the help of a built-in chatbot system.

The midlevel controller is the Arduino Nano, which handles the control of hardware and actuation of the motors on the low level. It is the Raspberry Pi that sends command messages to it through the serial communication channels and converts them into physical actions. The L298N motor driver module is used as a connection between the DC motors and the Arduino, making the wheels be able to move in all directions. This helps the robot to move within the farm field and align in taking the best leaf images.

The HC-05 Bluetooth module, which is connected to the Arduino Nano, establishes wireless communication between the user and the robot using the mobile device of the user. This module enables the farmers to remotely control the robot by voice or a mobile application. The detected

result of the processed disease with feedback is relayed back to the farmer through the Bluetooth speaker.

The Li-Po batteries are used to attain power management in two. The motor driver and Arduino Nano have a 2200 mAh battery, and the Raspberry Pi 4 and its peripherals are powered by a larger capacity 3000 mAh battery. To stabilize the voltage supplied by the batteries and to reduce it to suitable operating levels, a buck converter is utilized to provide a steady and efficient supply of power to all the modules.

In general, this circuit design forms a team system with the Raspberry Pi being concerned with calculation and communication and the Arduino Nano with the movement and actuation. Vision, speech, and control units are integrated to enable AGRIBOT to operate independently, which includes taking pictures in the field, identifying diseases, traverse the field, and reporting findings to the farmer in a small and energy saving system.

4.2.5 Comprehensive Hardware Integration

The AGRIBOT hardware architecture is based on a **master–slave communication model**, where the **Raspberry Pi** functions as the **master controller** and the **Arduino** acts as the **slave**.

1. The Raspberry Pi performs the computations of AI, data management and interaction with the user, and outlines time-sensitive operations like motor control and sensor surveillance to the Arduino.
2. The two devices communicate via serial communication (UART), and thus the communication between them is reliable.
3. Further expansion can also be made by use of the integration in future like connecting to cloud servers through Wi-Fi to enable remote monitoring and data analysis.

The hardware design of AGRIBOT was based on the principles of cost-efficiency, assembling, and modularity. All the system was constructed on the parts that can be easily found on the local market and thus it can be replicated and repaired by non-experts.

4.2.6 Hardware Development

The hardware design of AGRIBOT was based on the agronomics of cost-efficiency, assembly, and modular design. Components that are easily accessible in the local market were used to develop the entire system making replication, maintenance, and repair to be done by non experts.

1. **Mechanical Design:**

AGRIBOT mechanical structure is made of a strong aluminum chassis to hold the battery, camera and sensor modules safely and balancing them during use.



Fig 24: Mechanical Design of Agribot

2. **Motion System:**

The four geared DC motors are incorporated into the motion system where each is driven by an L298N H-Bridge motor driver, which has sufficient torque and traction to negotiate the irregular farmland land surface.



Fig 25: Motion System of Agribot

3. Processing Unit:

AGRIBOT processing structure consists of three main computational components, namely a Raspberry Pi 4, and an Arduino Nano. Raspberry Pi 4 is capable of making high-level decisions, artificial intelligence calculation and database management. Arduino Nano is the part that does low level control tasks like motor activation and navigation through Bluetooth thus providing remote monitoring and control.

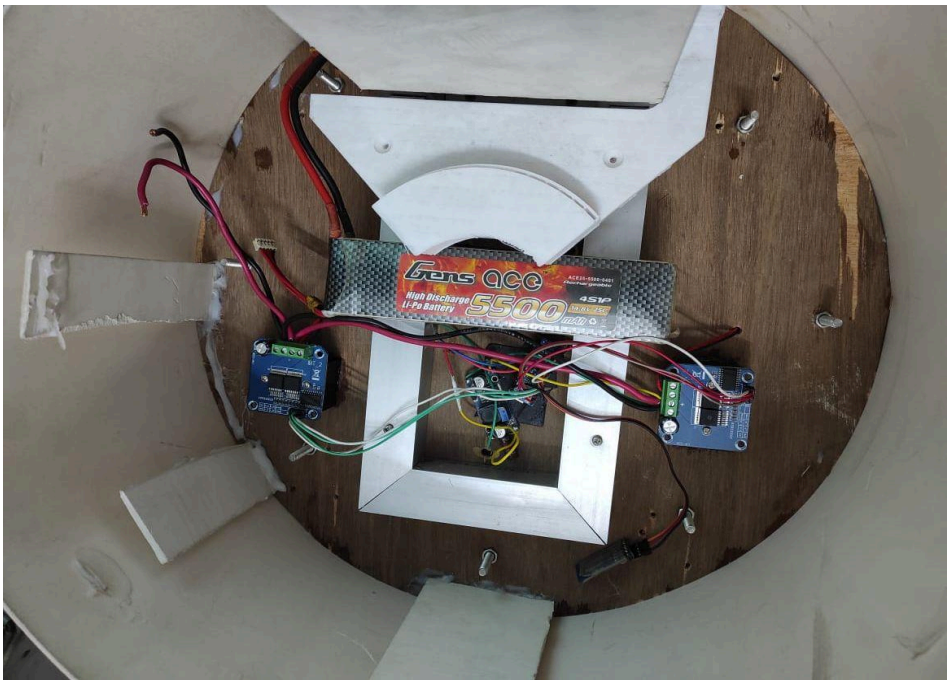

Fig 26: Processing Unit of Agribot

There are other peripheral devices that are fitted on the AGRIBOT to facilitate its interactive and operational features. Image capture is performed by a camera module, two-way voice interaction with the farmer is provided by a microphone and a speaker, pump and sprayer units can be applied automatically and controlled by a servo-motor by means of a relay, which provide automated irrigation and pesticide application.

A 12V 2200 mAh LiPo battery provides power to the system, which is enough to work much longer in the field. A step-down converter supplies a regulated 5V output that is constant to drive logic-level circuits, including the Raspberry Pi and Arduino. The individual hardware modules were also tested separately before their actual inclusion to achieve system reliability, stability, and safety in the field.

4.3 Software Design

The AGRIBOT software design is aimed to construct a transparent, modular, and smart system that is able to identify and react to mango leaf disease in real-time and communicate with farmers. It is an interactive software combining artificial intelligence, computer vision, speech processing, and database management. Such design guarantees scalability, flexibility and future expansion with ease to accommodate the new features like mobile integration and cloud synchronization.

4.3.1 Design Philosophy

The AGRIBOT is designed in terms of a modular and layered design in which each of the software units has limited functionality yet it is linked to the entire system. A given module is able to be updated or changed without affecting other sections of the system. The key principles of design are:

1. **Lightweight and Efficient Models**:

The deep learning applications will be optimized to work with Raspberry Pi 4. The system can take images locally without the use of massive resources of a GPU because lightweight Convolutional Neural Networks (CNNs) are used. Pruning and quantization are some of the optimization methods that can minimize the time spent on computation without compromising accuracy.

2. **Modular Python Architecture**:

The whole program is written in Python and separated into separate files e.g. disease_detection.py, voice interface.py.. This easy to maintain, debug and upgrade part of the scripting can be done easily since it is modular.

3. **Cross-Platform Compatibility**:

In spite of the fact that the major part of the work of AGRIBOT is based on a Raspberry Pi, the software architecture enables it to communicate with Android-based mobile applications and cloud-based solutions. This guarantees flexibility and enhanced accessibility in the future upgrades.

4.3.2 Software Architecture

AGRIBOT has a total software architecture that is broken down into three primary levels that are Client/Communication Layer (Tier-1), Software Layer (Tier-2), and Hardware Layer (Tier-3).

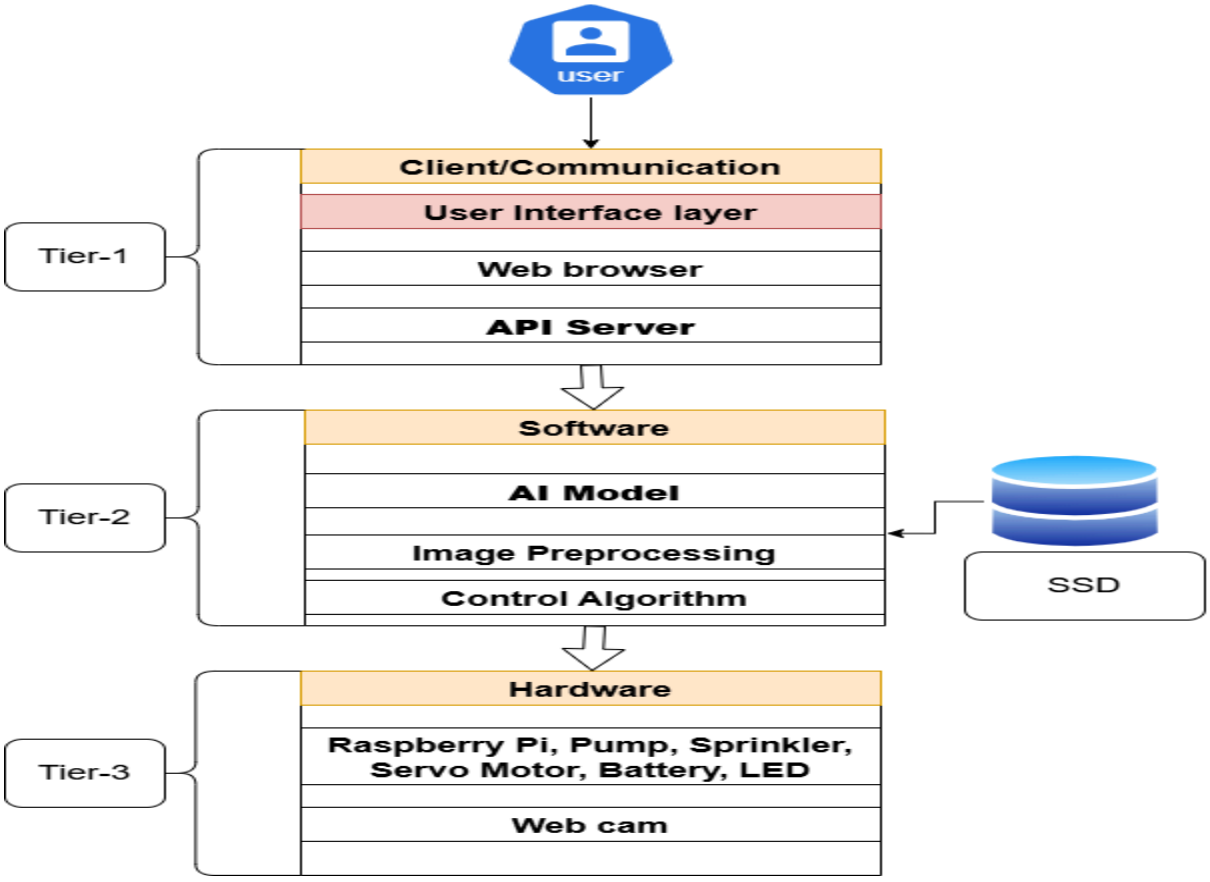

Fig 27: Software Architecture of Agribot

The three-tier structure separates user interaction, software processing, and hardware control to improve modularity and maintainability.

Tier-1:Client/Communication Layer

This layer is the interface between the user and the system. It consists of the User Interface which may be reached via a web browser or desktop GUI and the API server that manages the communication between the client and the software modules. This layer involves the sending of commands or queries by the user and the system then responds to it either visually or through voice.

Tier-2: Software Layer

This is the core of AGRIBOT's intelligence. It includes three main parts:

1. AI Model: Is a disease detector that uses CNNs that are trained on mango leaf-data.
2. Image Preprocessing: Handles noise removal, resizing, and color normalization using OpenCV.
3. Control Algorithm: Samples the results of the model and instigates actions, e.g. translates the commands to the hardware to spray or record information.

The information that has been processed is stored in the SSD database where the information on disease detection results and operational logs are stored to be analyzed later.

Tier-3: Hardware Layer

This layer is the one that has the actual physical components that come into contact with the environment. It consists of Raspberry Pi, camera module, pump, sprinkler, servo motors, LED indicators and battery system. The camera records images of the leaves, and they are checked on the AI model in the upper layer. According to the outcome, the Raspberry Pi manages the actuators correspondingly.

This three level design renders the AGRIBOT system modular and expandable. The layers are able to be updated or replaced individually.

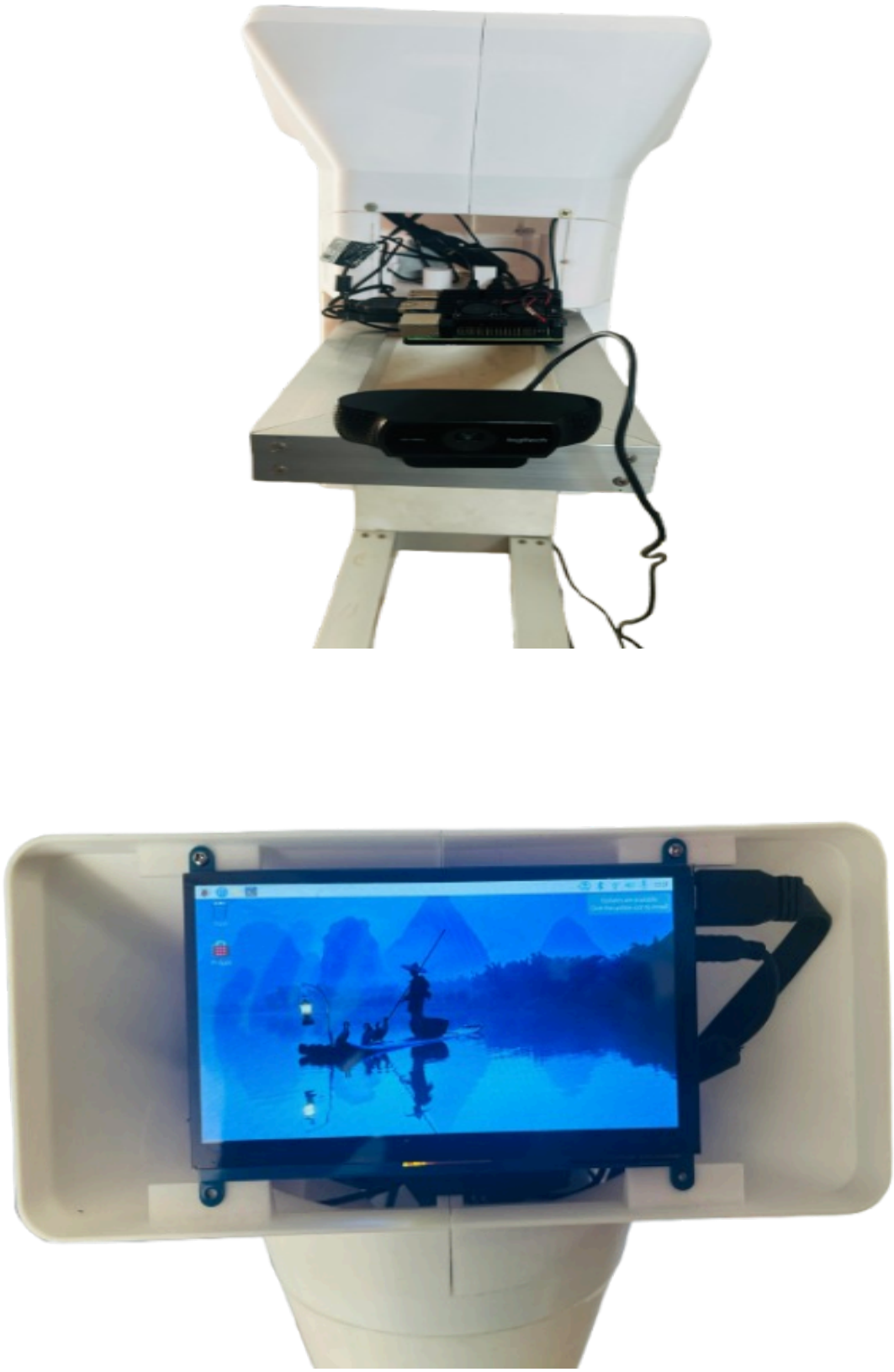

Fig 28: Hardware Layer of Software Integration

4.3.3 Software Layers

The AGRIBOT software is structured into a few functional layers in order to make the software easy to understand and to have clarity and correct communication between hardware and user interfaces.

1. **Operating System Layer:**

Raspberry Pi works with the Raspbian Linux operating system that offers a stable environment to high-level applications. At the same time, the Arduino controller uses embedded C firmware for low-level motor control and real-time sensor operations.

2. **Application Layer:**

The core application package is written in Python and it includes modules of CNN disease detection, speech recognition and database management. The CNN model is trained and executed with the help of TensorFlow/Keras frameworks, whereas image preprocessing and analysis are done with the help of OpenCV.

3. **Core AI Layer:**

This layer does the disease detection with the aid of CNN model developed with TensorFlow and Keras. The model is trained to classify different mango leaf diseases such as anthracnose and powdery mildew. Even with a small dataset, fine-tuning and transfer learning methods are used to enhance the performance.

4. **Computer Vision Layer:**

The OpenCV library takes care of the image processing operations, and these are image resizing, noise removal, and color normalization. It also facilitates real time video streaming, which enables AGRIBOT to detect leaves in real time rather than taking still images alone.

5. **Speech and Interaction Layer:**

The layer facilitates communication between the farmers and the system. It applies the Vosk library to Automatic Speech Recognition (ASR) to comprehend both the Bangla and the English commands. The responses through text-to-speech (TTS) are created using eSpeak-NG so that

AGRIBOT can respond orally. Simple Natural Language Processing (NLP) is also provided to process user input and invoke corresponding system responses.

6. **Database and Interface Layer:**

AGRIBOT stores detection results, timestamps and system logs in SQLite or MySQL databases. Each camera feed, disease classification result, and system status are displayed in real-time with the aid of the graphical interface written using Tkinter.

4.3.4 Development Process

AGRIBOT had a software development process that was based on Agile Prototyping, which focused on rapid development, testing, and user feedback.

1. **Incremental Development:**

The development was made of phases where each phase specialized in one of the subsystems including image processing, voice recognition, or database integration. This allowed it to be stable when adding new features.

2. **Field Testing and Feedback:**

The pilot projects were run in areas like Feni, Gazipur and Rajshahi. The voice commands were enhanced by feedback of people who used them to clarify the voice recognition and change the GUI design and even the response timing.

3. **Continuous Integration:**

Frequent testing was done to maintain the compatibility of all the components, Raspberry Pi, Arduino, and the mobile app, minimizing the risks of hardware and software errors.

4.3.5 User Interface

The primary interface runs on the Raspberry Pi using Tkinter. It gives live preview of a video, displays the results of the disease classification with percentages of confidence and offers the previous detection history. The interface also displays color-coded results, i.e., healthy leaves are displayed in green and infected leaves in red, as well as manual buttons, including, but not limited to, Scan Leaf, Spray, and Stop. It has both Bengali and English text options in order to be easier to use.

4.3.6 Voice and Multimodal Interaction

AGRIBOT promotes multimodal communication through the integration of speech, visual and audio communication. The system allows farmers to communicate via voice. For example, a farmer can ask in Bangla, “পাতায় কী রোগ?” (What disease is on the leaf?), and the system will take the live image, diagnose the disease, and give both oral and visual responses. This aspect renders AGRIBOT more inclusive and user-friendly to users who might be not well conversant with computers and touchscreens.

4.3.7 Planned Upgrades

The software design enables the improvements in future without the need of modifying the core system. Planned upgrades include:

1. **Cloud-Based Data Storage:**

The data on disease detection and associated environmental parameters will be uploaded to a cloud server to be stored in the long term and analyzed in terms of predictive analysis.

2. **AI Chatbot Support:**

An in-built chat robot will be provided to assist the farmers with general farming guidance like treating diseases, applying fertilizers and season maintenance.

3. **Expert Consultation Feature:**

This system will enable the agricultural experts to access real-time data and give feedback remotely, enhancing decision making and disease control at farm level.

4.4 Algorithm Development

The intelligence of AGRIBOT is based on algorithmic design that allows it to feel its environment, comprehend the nature of complex agricultural situations, and make independent decisions. It has a software architecture that incorporates various algorithms that interact with each other to control disease detection, speech-based interaction, and Controlled navigation. These algorithms are closely synchronized with the subsystems of hardware, which makes AGRIBOT an intelligent, self-dependent agricultural helper. The main algorithm structures that have been created in this system are the Convolutional Neural Network (CNN)-based disease detection engine, the Automatic Speech Recognition (ASR) and Keyword Spotting engine, and the Controlled Navigation algorithm.

4.4.1 CNN-Based Disease Detection

The core of the entire process of intelligent decision-making in AGRIBOT is a Convolutional Neural Network (CNN), which was specifically trained to detect and classify the mango leaf diseases. The CNN-based system allows the robot to analyze the images of leaves it has captured with great accuracy and identify the health status of the leaf.

4.4.1.1 Overview of CNN Workflow

The general pipeline of the CNN-based plant disease detection process can be considered to have four significant stages which are dataset collection and processing, model selection and training, model performance evaluation and result interpretation. All the phases are meant to guarantee the effective and effective disease detection even when it is in tricky field conditions.

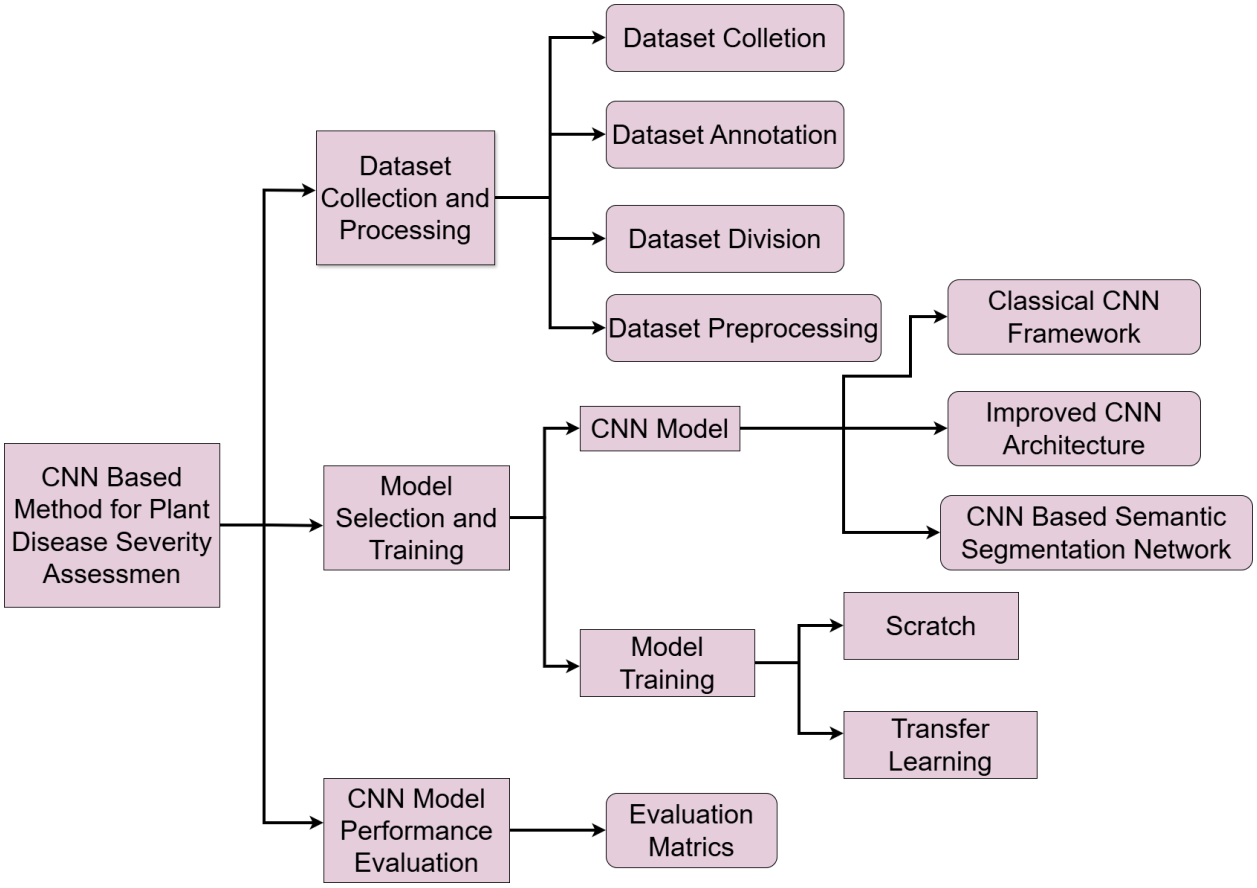

Fig 29: Flowchart of CNN-Based Plant Disease Detection Severity Assessment

4.4.1.2 Dataset Preparation

It has created a special dataset of mango leaf images, with about 4,000 images, which were categorized into eight groups, namely, Anthrocnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Sooty Mould, Healthy. The camera in the robot was used to take pictures in various natural light sources and backgrounds to guarantee high robustness and ability to withstand variability in fields.

4.4.1.3 Image Preprocessing and Augmentation

Preprocessing steps like resizing, normalization and background removal were employed to increase the diversity of the dataset by eliminating overfitting. The variation of data processed through image augmentation techniques, such as random rotation, horizontal and vertical flipping, zooming, and change of brightness was applied to augment the data variation without requiring more data to be collected.

4.4.1.4 Model Architecture

The CNN model was composed of several convolutional layers and max-pooling layers to extract features, ReLU activation functions that provided non-linearity and fully connected dense layers to classify. The last output layer incorporated the Softmax activation to classify the images into eight disease categories. Adam optimizer was used in training the model with categorical cross-entropy loss, and optimal convergence was achieved with the help of multiple epochs.

4.4.1.5 Performance Evaluation

The trained CNN achieved an overall accuracy of approximately 90% on the validation dataset. During real-time deployment on the Raspberry Pi 4, the average inference time was between 1-2 seconds per image, ensuring timely disease detection without significant processing delay. The findings showed that the CNN could be used to carry out correct classification even during variable field conditions.

4.4.2 Keyword Spotting and ASR Processing

4.4.2.1 Overview of Speech Command Recognition

AGRIBOT also includes a speech recognition command system through which the farmer can engage the robot in a natural conversation using their voice. Automatic Speech Recognition

(ASR) is a module that has been designed around a Keyword Spotting (KWS) mechanism that constantly monitors the trigger words with respect to the operational tasks. This lightweight approach is optimized for embedded systems such as the ESP32 and Raspberry Pi 4, ensuring low-latency performance even with limited computational resources.

The general flow of the pace of the key-word spotting process illustrates how the system takes audio input, processes it to identify the key-word and trigger related robot operations.

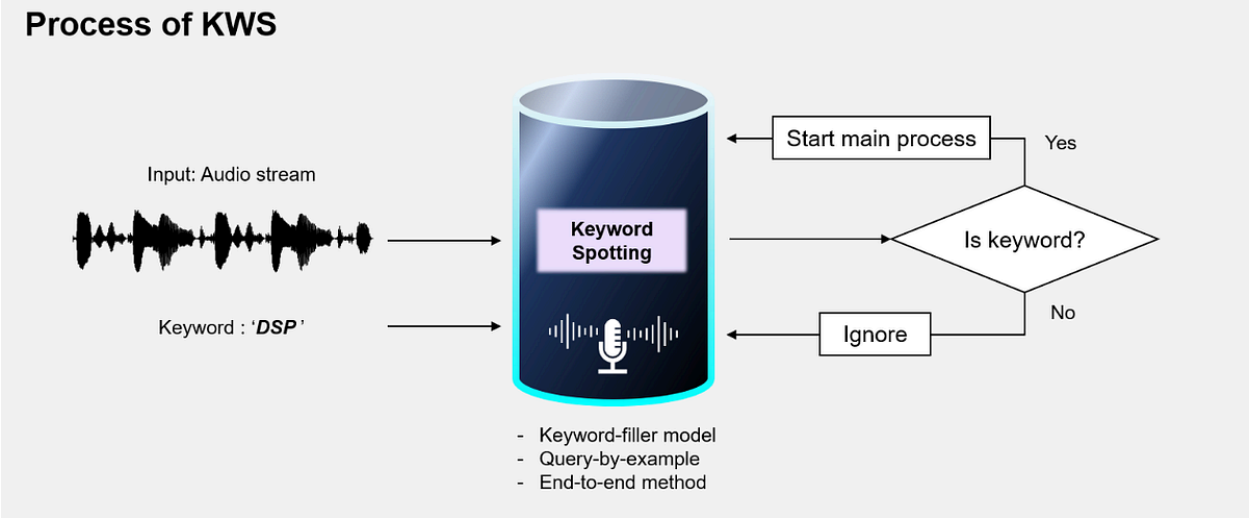

Fig 30: Process flow of the Keyword Spotting system [92]

As depicted in the figure, the KWS module gets a continuous audio stream on the onboard microphone. Digital signal processing (DSP) operations which include noise reduction, framing, and feature extraction using Mel-Frequency Cepstral Coefficients (MFCCs) are used to preprocess the incoming audio. Comparison of the extracted features with a preset keyword database is then done. When the sound pattern that has been identified is similar to a registered keyword (e.g., scan, irrigate, or stop) the system itself confirms that it is a valid command and it executes the corresponding main process. If no keyword is detected, the input is ignored to minimize false activations.

4.4.2.2 Keyword Detection Mechanism

ASR engine used a lightweight keyword spotting algorithm that was able to identify the particular operational commands like; scan leaf, start irrigation, move forward and stop. The

individual keywords were then mapped to a predetermined robot functional in the command dictionary after being identified.

4.4.2.3 NLP Post-Processing and Command Mapping

After identifying a keyword the system uses the Natural Language Processing (NLP) module to understand the context and purpose of the command. All known keywords are associated with a set of robot functions that are hard-coded in a command dictionary. To illustrate, the keywords scan the leaf or disease check would initiate the image capture and disease detection module whereas the key words start irrigation would ignite the water pump that is controlled by a relay. To minimize unintentional or unplanned activities, the NLP post-processing layer ensures that the input is matched with a legal operational context and is executed beforehand.

4.4.2.4 Bilingual Voice Interaction

The system has provisions to facilitate the use of either Bengali or English to local farmers to improve accessibility. The bilingual design was implemented by two key word collections and language specific preprocessing systems. AGRIBOT is able to automatically transition between languages depending on the language speech pattern, and thus has a more user-friendly and inclusive interface.

4.4.3 Navigation System

4.4.3.1 Overview of Navigation Framework

The manual navigation system forms the foundation of the AGRIBOT's mobility. This module allows the robot to be operated entirely by a human user through a remote interface. This design relies on the operator's decision-making to navigate the agricultural field. The robot executes the exact movement commands sent by the user. The primary goal of this framework is to provide a responsive and low-latency driving experience, allowing the operator to navigate the robot precisely in the Mango tree orchards.

The process is straightforward: the operator inputs a command (speed and direction), and the robot executes it immediately.

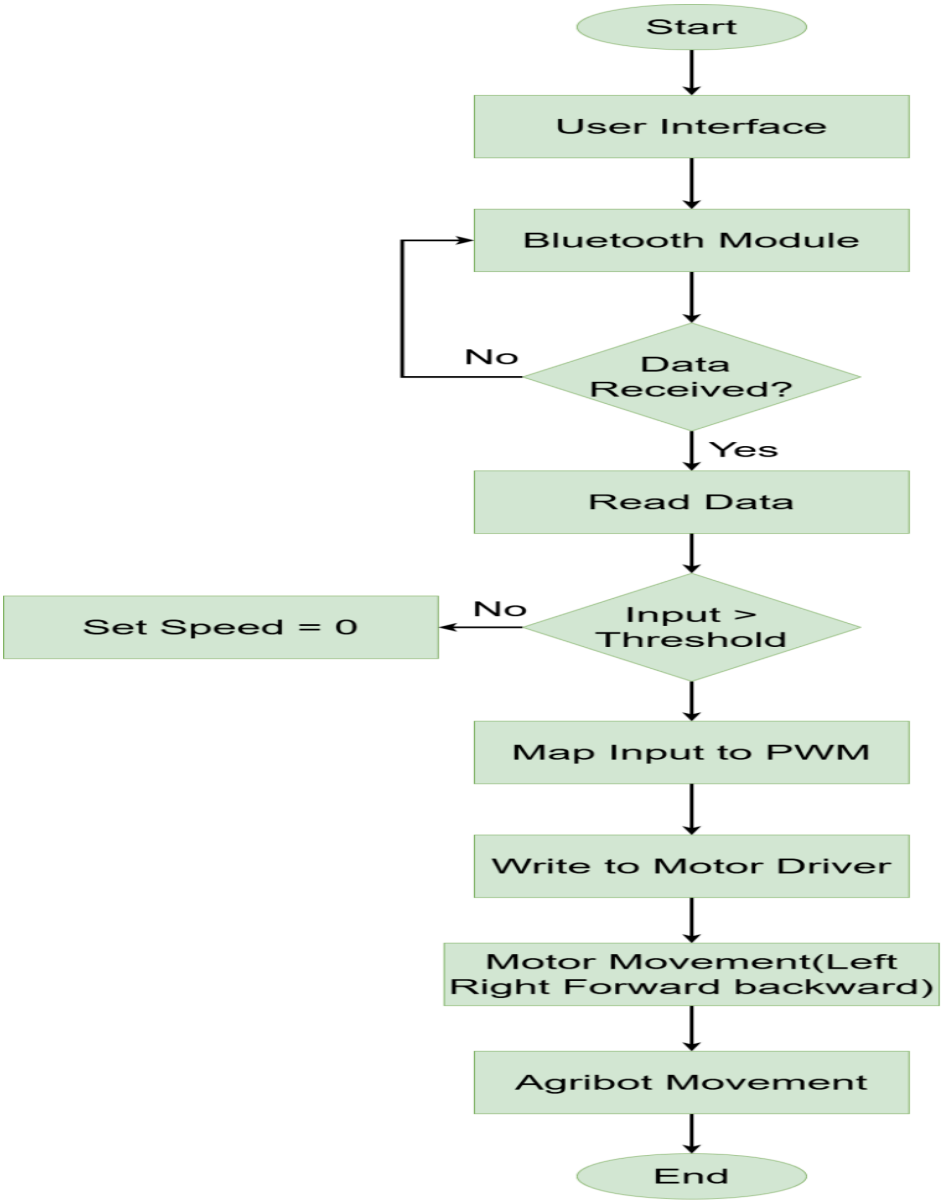

Fig 31: Flowchart of navigation process of Agribot

4.4.3.2 Wireless Communication Interface

The robot is equipped with a wireless Bluetooth module that acts as the receiver. It listens for control signals sent from the operator's mobile application or handheld controller. This module ensures that the connection remains stable. It also allows for real-time transmission of steering.

4.4.3.3 Input Interpretation and Safety Override

This is the core of the RC algorithm. The system operates on a Check then Act logic.

1. Input Receive: Arduino Nano works as a Receiver through the Bluetooth module. Arduino Nano receives vector commands of navigation or change of speed.
2. Signal Parsing: The algorithm reads the inputs and determines whether to move forward backward or to change direction or to increase or decrease the speed.

4.4.3.4 Motion Execution

Once the control signals are calculated, they are converted into physical motion. The Arduino Nano generates Pulse Width Modulation (PWM) signals which are sent to the L298N motor driver. The driver then sends power to the DC motors. This control loop allows the user to easily change the speed of the AGRIBOT, enabling both slow, careful inspection and faster movement across the field.

4.4.4 Integrated System Intelligence

AGRIBOT is a Controlled Navigation based system, which is based on the integration of CNN-based disease-detection, ASR-driven voice-control, and controlled navigation. These algorithms combined to form a self-perpetuating mix of feeling, perception, and response. The CNN displayed visual intelligence of identifying the diseases, ASR system allowed human interaction by voice and the navigation algorithm enabled safe and efficient movement. They both made AGRIBOT an intelligent assistant that can make real-time decisions and act in ways that are adaptable in dynamic agriculture settings.

4.5 System Workflow

AGRIBOT system workflow is the entire process of operation starting with the user input and finishing with giving intelligent and actionable output. It shows the interaction of software and hardware modules to form a complete network of data communication and reaction to a disease in real time, voice communication, and autopilot functioning. The workflow is the plan of processes and how they are interrelated.

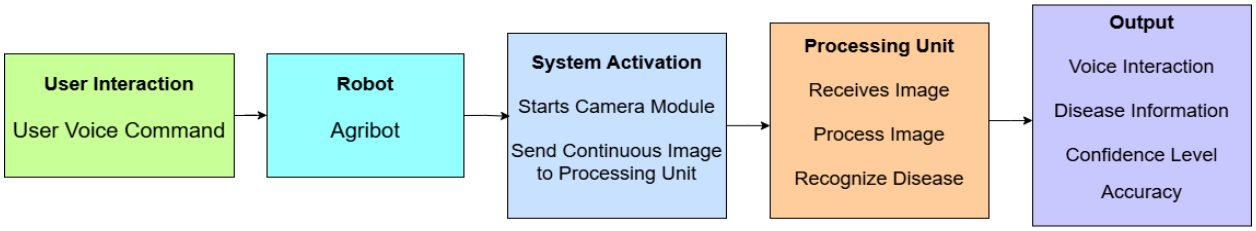

Fig 32: System Workflow diagram of Agribot

1. **User Interaction**

It starts with interaction with the user whereby the farmer makes a voice command to AGRIBOT by using predefined keys in Bengali or English. The Automatic Speech Recognition (ASR) system on board does the interpretation of the spoken input and translates it into a digital command. Such design makes communication possible without hands, which comes in especially handy in the farming area where the manual input is inconvenient.

2. **Robot Activation**

After the recognition of a valid command, the AGRIBOT goes to the system activation stage. At this phase, the robot starts the hardware modules needed in accordance with the received command. To detect the disease, the AGRIBOT will trigger the camera module which would then capture image of the plant leaves continuously and send the image to the processing unit to be analyzed. The hardware (camera, motors, sensors) and software (control logic, CNN model) are coordinated by the serial communication and GPIO interfaces, which are also the means of synchronization of the work.

3. **Image Processing and Disease Detection**

AGRIBOT functions in the processing unit which is the core intelligence. The Raspberry Pi 4 runs the Convolutional Neural Network (CNN) model that performs several sequential tasks:

i. Receiving and preprocessing the captured images (resizing, noise removal, normalization).

ii. Comparing the features of the processed image with the stored database of the known disease-classes

iii. Determining the disease and estimating the confidence level and the prediction accuracy of the result of the classification.

This is an automated image analysis that allows AGRIBOT to identify plant disease at high speeds and precision within a range of light and environmental conditions.

4. **Output Generation and Feedback**

Once the disease is detected, AGRIBOT produces an output response both visual and auditory. The name of the disease and its level of confidence as well as any recommendation is communicated to the user through voice recognition mechanism installed on the device. Also, the identified findings may be recorded locally or sent through the Wi-Fi to a mobile or cloud-based surveillance system.

This is a closed-loop interaction among users, software and hardware to provide continuous interaction and intelligent decision-making. AGRIBOT does not just analyze environmental data independently, but it also conveys the information in a user-friendly format.

To conclude, the workflow of AGRIBOT is characterized by the combination of perception, processing, and communication into one system. Starting with the input of the user, the robot gathers and processes the information on its own and provides feedback with valuable results.

4.6 Environment Design

4.6.1 Imaginary Scenario

The Agribot is designed to navigate through the mango farms in Bangladesh. The Agribot is imagined to work with smart farmers who can use the device in mango fields to navigate and detect the disease of mango trees by analyzing the tree leaves.

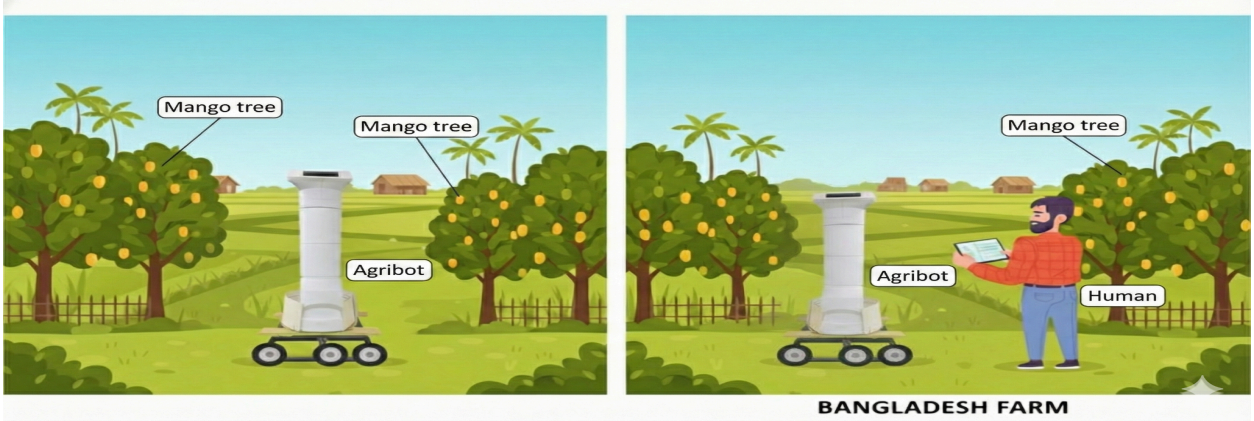

Fig 33: Imaginary Environment of Agribot



Fig 34: Imaginary Scenario of Agribot Working with Farmer

4.6.2 Real Life Scenario

Agribot was taken to the Mango farm to test the real life results to validate its performance under realistic agricultural conditions. The test was conducted at Dhaka in a Mango farm during daylight to check the detection accuracy of Agribot with higher light intensity. The matrices such as the accuracy, navigation reliability, response time was recorded during the test along with the user satisfaction and comfort.



Fig 35: Real Life Scenario of Agribot



Fig 36: Operating Agribot in Real Life Scenario

CHAPTER 05

Implementation

5.1 Hardware Setup

5.1.1 Components and Connections

Agribot hardware architecture will have a Raspberry Pi 4 to process high level control, an Arduino Nano to control irrigation hardware, and a list of peripherals to sense, actuate and move.
Key components used:

1. Raspberry Pi 4 (4GB)
2. Arduino Nano
3. Logitech C922 Pro webcam
4. L298N DC motor driver
5. HC-05 Bluetooth
6. microphone modules
7. Bluetooth speaker
8. Power supply unit

Image processing and disease classification are done with the CNN model to the Raspberry Pi. In case disease is identified with enough confidence over a long period, the Pi transfers a serial command to the Arduino. Arduino will switch on the pump and operate irrigation devices through the relay.

5.1.2 Assembly Diagram

The mechanical structure of AGRIBOT was built in a modular form in such a way that every part is replaceable or upgradeable on its own.

1. The camera and Raspberry Pi module are fixed on the top surface so that the surfaces of leaves can be seen correctly.

2. The sprinkler assembly and the pump of water are placed at the center where the irrigation output is steady.
3. The Arduino is put close to the relay to minimize the wiring and the noise.
4. To ensure a low center of gravity, motor drivers and batteries are put at the bottom platform.

The assembly diagram shows the internal layer distribution, cable routing, and mounting brackets.

5.1.3 Images of the Robot

Prototype Testing

The simplest Robot Prototype model and validation of the CNN prediction with camera alignment.

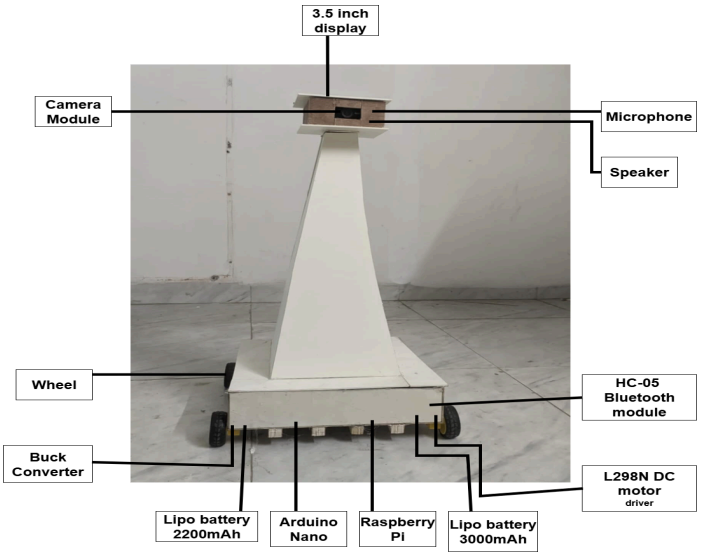

Fig 37: Prototype of Agribot

Agribot Robot Image

Stabilized wheeled, cable shielded, and enhanced irrigation performance.



Fig 38: Image of Agribot

5.2 Software Implementation

The software at AGRIBOT is structured into three main modules whereby each module takes care of various issues concerning real-time disease detection and irrigation control. These modules together guarantee consistent and dependable functioning between data gathering and actual irrigation reaction.

Image Processing and Classification module is a Python program based on the Raspberry Pi that is used to capture real-time video through the Logitech C922 Pro webcam and prepares the frames to be analyzed. The system uses a number of preprocessing stages, such as resizing to match the model input size, normalization and HSV masking to remove non-foliage areas. Once the frame is preprocessed, the frame is inputted into the CNN classifier, which anticipates whether the leaf is diseased or healthy based on a 90% confidence threshold. The system will not send an alert until 15 seconds of consistent detection of the disease is noted to enhance

reliability. When this condition is met, an alert about the disease is transmitted to the Arduino to take physical action.

The Irrigation Control module is an Arduino C++ implementation which receives the detection signals transmitted through the serial by the Raspberry Pi. The Arduino, using these commands, turns on a relay which turns on the 12V irrigation pump. In case of disease confirmation, the servo-controlled rotating sprinkler would start water spraying the affected area. The module guarantees the accurate timing, secure running of pumps and fluent rotation of the irrigation mechanism.

Lastly, the IoT Synchronization Layer takes care of the consistency of the communication between the Raspberry Pi and the Arduino. It assures that the commands are properly passed and received even when conditions in the environment or power fluctuate. Scalability is also provided by this layer, later iterations of the system can add Wi-Fi-based monitoring dashboards, cloud storage of the captured pictures of the leaves, and SMS to farmers. AGRIBOT is simple to expand into a full IoT-based agricultural management platform due to its modular nature.

5.2.1 Code Structure

The software is modular and it is split into preprocessing, prediction, communication, and actuation modules. The python code structure is divided into distinguishable scripts of camera capture, CNN loading, frame preprocessing, disease detection logic, and serial communication handlers. The code has been organized on the Arduino side, in terms of pump control methods, servo control loops, and safety check conditions.
The sections are also made to be testable with ease of isolating during testing, thus making it easier to debug and increase maintenance.

5.2.2 Key Functions

Key functions include:

GPIO Setup: Initializes relay control, camera access, and serial communication ports.
Image Capture & Preprocessing: Converts frames to suitable resolution, normalizes pixel values, and applies HSV masking to focus on green leaf regions.
Disease Detection Function: CNN prediction becomes active, confidence thresholds are tested and 15-second time filtering is used to filter false positives.

Irrigation Control: Pump and sprinklers will be activated to water the target area, in case of disease confirmation.

Error Handling: Handles communication delays, camera errors, and hardware response failures.

5.2.3 System Pseudocode

Image Preprocessing Function

```
def preprocess(image):
    resized = resize(image, target_size=(64, 64))
    hsv = convert_to_hsv(resized)
    masked = apply_hsv_mask(hsv)
    normalized = normalize(masked)
    return normalized
```

Disease Detection Logic

```
def detect_leaf_disease(image):
    preprocessed = preprocess(image)
    result = cnn_model.predict(preprocessed)
    return result
```

5.3 Voice Interaction

The AGRIBOT voice interaction subsystem is useful in improving the accessibility of the system to users, as it allows farmers to use it hands-free and is also bilingual. In this module, speech recognition, text-to-speech (TTS), and an AI-based conversational engine have been incorporated to enable smooth interaction between the user and the robot. The interaction pipeline was built in a way that would allow the user to request system status, disease information, and troubleshooting instructions in natural speech and therefore the system was tailored towards rural agricultural settings where it is vital to have ease of use.

The voice interaction software has a modular architecture based on Python-based speech libraries, OpenCV-assisted image processing triggers, and the Gemini AI conversational model. All the modules are autonomous and they look at each other via a central workflow controller.

The design enables the effectiveness of future gains in recognition, support of new languages or integration with offline TTS/ASR engines without impacting on other system components.

5.3.1 Robot Interaction Model

The structured conversation loop that constitutes the foundation of the interaction model includes language detection, service routing as well as the LED-based visual feedback. Due to its modular nature, the system would be able to assist the user visually and audibly.

The Block Diagram of Robot Interaction Model of the agricultural robot reveals the way the orders of farmers are translated into valuable functions and responses. The process starts with the speech module with the input of the farmer. This input may be delivered through manual instructional entry or speech voice command. The main controller which is the central component of the system decodes the input and directs it to the appropriate module. In terms of the health of crops, the command is sent to the image processing module. This module compares the images of the leaves and identifies potential diseases with the help of CNN model. The main controller sends the AI Chatbot module the commands in the form of questions and explanations. Thereafter, the chatbot replies with an appropriate text or voice message. The speech module gives the farmer the response in an ordinary everyday language provided by a chatbot. And upon the discovery of the plant disease that consists of the conjunctival support, this loop takes the form of a closed loop system, which plays a significant role in the successful communication between the robot and the farmer.

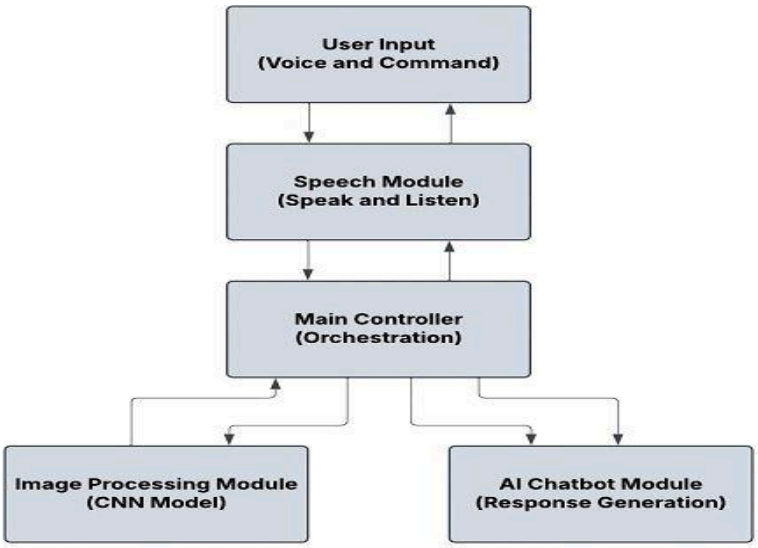

Fig 39: Block Diagram of Robot Interaction Model

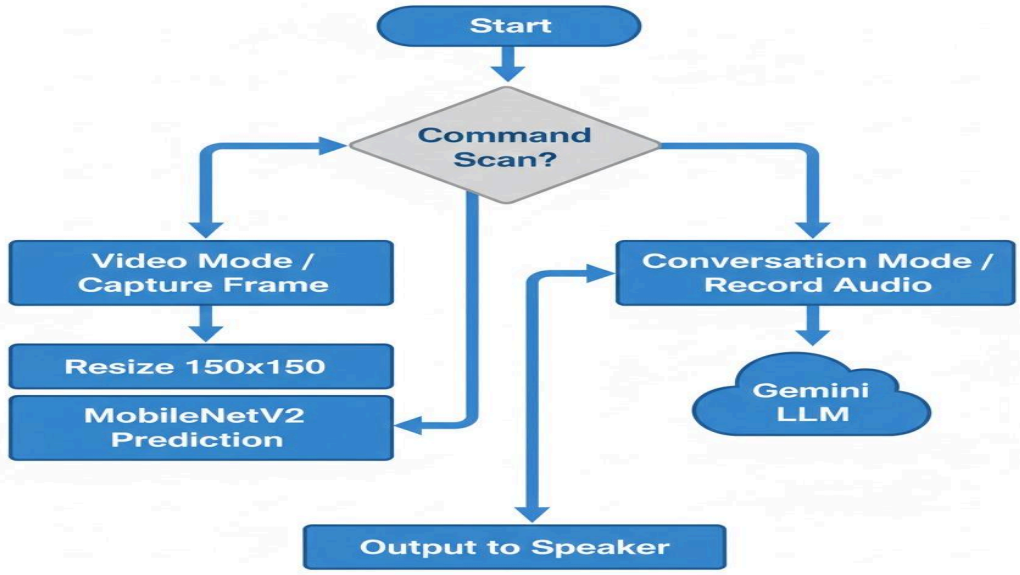

Fig 40: System Workflow of Agribot

5.3.2 Speech Recognition Module

The Speech Module will handle voice command capturing and transforming it into text. It employs Python SpeechRecognition library and sensitive microphone input which is sensitive to outdoor noise conditions. Upon starting the interaction, the audio samples are recorded by the microphone and preprocessed in order to eliminate the background noise and harmonize the levels of the volume. The module tries to make the speech-to-text conversion and in case of any error (poor interpretation of the command, wind noise or silence), the module will automatically perform correction measures like repeating the listening cycle or asking the user to repeat.

Particular consideration is made to robustness, and the agricultural conditions usually have environmental noise, such as wind, birds, or motor vehicles. To overcome these difficulties, the module employs adaptive noise thresholding and requests repetitions. After the verbal command has been effectively transformed into the textual format, it is sent to the main controller module to be processed further.

5.3.3 Text-to-Speech (TTS) Response Module

To deliver audio feedback, the system uses the Google Text-to-Speech (gTTS) engine to convert textual outputs into natural-sounding speech. This makes sure that farmers are not

subjected to reading the text on the screen. The TTS engine is programmed to accept both Bengali and English for the highest possible accessibility by the locals.

Audio feedback would comprise: outcomes of disease detection, irrigation status reports, system notifications and alerts, user questions answers through the AI chatbot.
The output of the generated speech is stored temporarily in the form of an audio file which is then played out through the speaker output of the Raspberry Pi. This module guarantees the easy to comprehend voice prompts even in noisy conditions.

5.3.4 AI Chatbot Module

The AI Chatbot module will incorporate the Google Gemini AI which will allow the system to interpret user queries and offer contextually appropriate explanations. The chatbot overcomes language barrier since it supports both English and Bengali languages and therefore, the system is farmer-friendly. The converted text is relayed by the speech recognition module, and the chatbot responds to it, which will be relayed to the TTS engine to be played out.

Response validation logic is also implemented in the module to make the outputs safe, relevant, and with respect to the agricultural purpose of the system.

5.4 Testing and Calibration

5.4.1 Testing Process

The testing was segmented into three stages, which included the laboratory testing, controlled environment testing, and real-field testing.

Lab testing: Validated the CNN model's responsiveness using stored images under controlled lighting.

Field testing: This was done in a working mango orchard to test long duration-performance, sunlight variability and irrigation precision.

Calibration entailed setting HSV thresholds to cope with various lighting conditions, setting servo rotation angle to achieve specific coverage and setting 15-second consistency threshold according to practice.

5.4.2 Challenges and Resolutions

A number of difficulties were faced and they included:

1. **Lighting variations:** Midday sunshine had an impact on accuracy of detection.

   Solution: Adaptive HSV thresholding and dynamic exposure settings.

2. **False positives from non-leaf objects:** Grass or background objects triggered detection.

   Solution: Increasing green-region filtering and updating preprocessing rules.

3. **Serial communication delays:** Occasional missed signals between Raspberry Pi and Arduino

   .Solution: Installed hand shake-based communication and retransmission.

4. **Water pump overheating:** The overheating of the pump was due to the continual use of the pump.

   Solution: Introduced cooldown cycles and extended relay protection.

Each issue helped refine the system's robustness for real-world deployment.

CHAPTER 06

Dataset

The **quality**, **diversity**, and **realism** of the dataset on which the **Convolutional Neural Network (CNN)** is trained are the keystones to the effectiveness of the disease detection system of AGRIBOT. Given that deep learning models require substantial sample data that is representative, to make well-informed predictions in the real world, a specialized dataset on mango leaf disease was designed in this project. The dataset was not only aimed at providing high accuracy, but also, the dataset should be representative of the conditions experienced in the environment and operations in real farmlands.

In contrast to publicly accessible resources like **PlantVillage**, which can be full of images taken in a laboratory, with good light, and perfectly oriented, the dataset in this project focuses on a real-world environment - and is variable in terms of lighting and shadows, occlusion, camera angles, and natural backgrounds. This will make sure that AGRIBOT will operate reliably in a wide range of outdoor conditions, as opposed to trying to act as a fairy tale.

6.1 Data Collection

The data set was gathered by means of both secondary (referral) and primary sources, providing a moderate combination of real world pictures and high-quality reference samples.

1. **Primary Data Collection**:
   Some of the pictures were taken when several field trips were made to mango orchards within the area of Rajshahi, Gazipur and Feni where large-scale mango production is a common practice in Bangladesh. Field measurements were measured on different conditions, i.e. morning, noon and evening, to consider the variability of illumination. A 1080p Pi Camera was used to take each of the images on the AGRIBOT prototype and a fixed distance and angle were maintained to keep the data sets constant.
2. **Secondary Data Sources:**
   Other pictures were collected in trustworthy online databases like PlantVillage, Kaggled, and agricultural research databases [99]. These additional samples increased the diversity of this dataset and balanced underrepresented classes.

6.2 Dataset Composition

The last dataset consists of about 4,000 images of the mango leaf, which are balanced in terms of eight categories representing both disease as well as the healthy condition.

Category	Description	Images
Healthy	Leaves with no visible infection, serving as baseline references.	
Anthracnose	Characterized by dark, irregular necrotic lesions caused by Colletotrichum gloeosporioides.	
Powdery Mildew	White fungal growth commonly seen on the leaf surface due to Oidium mangiferae.	
Gall Midge	Gall midge larvae feed within plant tissue, causing abnormal plant growth called galls that can damage mango leaves, flowers, fruit and shoots.	
Bacterial canker	Water-soaked lesions and tip burn caused by Xanthomonas campestris pv. mangiferaeindicae.	

Sooty Mould	a black, powdery to crusty fungal growth that coats plant leaves, stems, and even outdoor surfaces, forming a film that looks like soot	
Cutting Weevil	a small, dull-colored beetle known for its distinctive damage to young mango foliage, where females use their snouts to make scissor-like cuts on tender leaves before laying eggs and dropping them to the ground, causing significant plant growth loss	
Die Back	a serious fungal issue, primarily caused by Lasiodiplodia theobromae	

6.3 Data Acquisition Tools

In order to collect high-quality and diverse image data, professional and easily accessible tools were combined in the process of data collection. The main imaging device was the **Logitech C922 Pro camera** that supports 1080p resolution and has an **HDR (High Dynamic Range)** feature. This camera, capable of giving clear images with a high level of detail, maintained delicate disease patterns in the form of changes in color, anomalies in texture and growth of fungi which were key to proper CNN-based classification.

Besides the primary camera system, Android phones belonging to local farmers were used as an alternative source of image gathering. This methodology not only expanded the size of the

data set, but also introduced natural variability in image composition, resolution and lighting conditions which assisted in making the CNN model more resilient to real-life variability. The fact that farmers were also allowed to be involved in this step helped in instilling a sense of ownership and awareness of what the project was all about.

The image capture sessions were purposely done with varied light conditions to ensure greater diversity of the environment; they were performed in direct sunlight, overcast weather and shaded orchard settings. This made sure that the information gathered was of realistic visual diversity including glare, shadowing, and asymmetrical lighting conditions that the robot would experience in real field performance. These well crafted acquisition plans render the dataset to be representative to real world agricultural settings thus enhancing more accuracy and reliability of AGRIBOT to detect diseases.

6.4 Data Preprocessing

Preprocessing of raw image data is an important task in preparing raw image data to be utilized in the successful training of CNN. The images collected were also taken using different cameras, under different lighting conditions, and against different backgrounds, therefore preprocessing was necessary to achieve uniformity, clarity, and appropriateness to model learning. It is an operation that will help reduce noise and improve the quality of the dataset and maximize the accuracy of feature extraction during the training process. The key preprocessing procedures of AGRIBOT dataset are as follows:

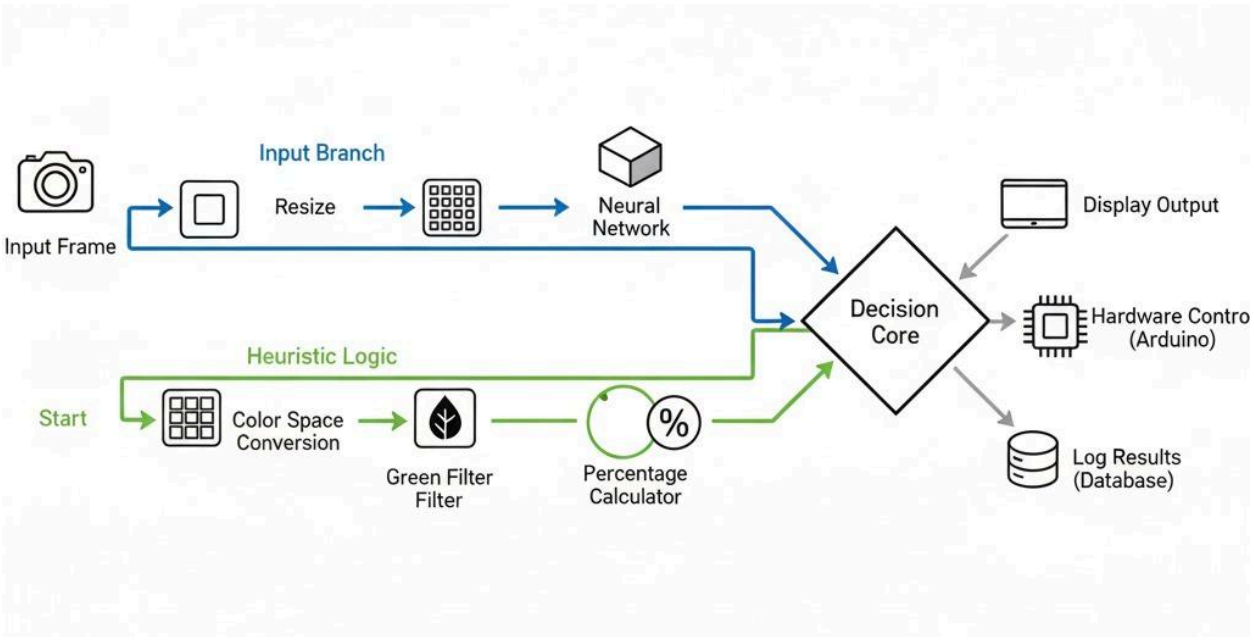

Fig 41: steps of Data preprocessing used in Agribot

1. **Image Resizing**

Each raw image was then scaled to a 224 by 224 pixels, a common input size of most deep learning architectures including VGG16, MobileNet and ResNet. Resizing guarantees consistency among samples as well as makes the CNN computationally simpler without distorting significant disease features. The fixed resolution is also beneficial to batch processing, and to make the network learn the same spatial patterns on all images.

2. **Noise Reduction**

Given that field images were recorded in varying conditions of lighting, some of them had visual noise in the form of dust particles, blurred motion of leaves, or uneven light. To correct these issues:

1. A **Gaussian filter** was used in order to smooth the image and eliminate noise of random pixels without blurring out significant details.
2. They were enhanced by **histogram equalization** to make sure that the areas of disease like darker spots, powdery texture or discolorations could be more visibly noticeable.

All these methods served to ensure the CNN model identified subtle patterns of diseases with greater accuracy because they increased the visual clarity of training samples.

3. **Segmentation**

This was an essential process of segmentation to separate the **leaf area** to the surrounding environment. Since the images in the field contained undesirable background (soil, sky or other vegetation) a **background subtraction algorithm based on Otsu thresholding** was introduced. The approach automatically gave the best threshold value that was used to distinguish the foreground (leaf) and the background. The output segmentation has been used to only learn on the relevant leaf surface in order to avoid the CNN picking up the wrong patterns due to non-leaf regions. This measure gave a humongous reduction in the possibility of false classifications caused by background interference.

4. **Normalization**

All pixel values were divided with 255 before feeding the images into the CNN to normalize pixel intensity values to a range of 01. Normalization enhances training stability, accelerates

convergence and makes the input features play equal contribution to the learning process. This was necessary to facilitate the smooth gradient change with model training.

5. Data Augmentation

In order to increase the generalization capacity of the model, data augmentation methods were used to increase the dataset artificially and to bring about controlled variability. These augmentations mimicked the real world scenarios including variation in the leaf orientation, position and lighting. In particular, random rotations of 0, 30 were used to simulate natural camera movement whereas horizontal and vertical reverses were used to simulate viewing angle variations. The scaling of 0.8x to 1.2x was applied to the same range to simulate changes in distance and cropping was turned on randomly to simulate close-up/partial captures of the leaves. Also, it added variations of brightness to up to 30 percent to compensate for changing brightness in field settings. Due to these changes, the size of the dataset grew to about 15,000 images out of the approximately 4,000 images originally that provided a more diverse and representative training data to the CNN model.

6. Dataset Balancing and Quality Assurance

Following augmentation, the size of each disease category was equalised in order to avoid bias in training. All the images were reviewed manually to ensure proper labelling and acceptable visual quality. Images that were blurred, overexposed and misclassified were ignored in order to preserve integrity of the dataset. This step of quality control was very careful, so that CNN models could learn correct and significant visual patterns.

7. Final Dataset Preparation

Lastly, all the preprocessed images were placed into respective folders based on the disease. The data was further divided into training (70%), validation (20%), and testing (10%) data subsets. This separation made it possible to evaluate the performance of CNN appropriately and also made sure that the model was tested according to unseen data.

In general, this entire preprocessing pipeline would turn a raw and heterogeneous set of field and online images into a clean, balanced and high quality dataset. These measures increased the performance of AGRIBOT in detecting leaf diseases in true agronomical environments even when the environment lighting, orientation or background varied greatly.

6.5 Analysis of Dataset

The obtained and preprocessed data were analyzed in such a way that it represents all the significant categories of mango leaf conditions of health adequately. The analysis presented the distribution, diversity, and statistical properties of the data to be used to train AGRIBOT Convolutional Neural Network (CNN). The data set included pictures of the healthy and sick leaves collected by various sources such as the field samples and publicly available data. The analysis was aimed at confirming the fact that the dataset was balanced, representative and highly visual variability so that the disease detection in the real world conditions is reliable.

6.5.1 Dataset Distribution

In order to avoid the possibility of bias in the model and to provide the same level of learning to all classes, the dataset was augmented carefully without compromising the proportionate representation of the classes. The table presents statistics of the images in various categories before and after augmentation.

Class	Original Images	Augmented Images	Total Samples
Healthy	600	1,800	2,400
Anthracnose	500	1,600	2,100
Powdery Mildew	400	1,400	1,800
Gall Midge	500	1,500	2,000
Bacterial Blight	500	1,200	1,700
Sooty Mould	600	1400	1900
Die Back	400	1200	1400
Cutting Weevil	500	1400	1700
Total	4,000	11,500	15,000

Following augmentation, it had **15,000 labeled images** in eight different classes. This comparatively balanced design indicated that the CNN model was not going to overfit or underperform in categories that were underrepresented. The constant number of samples in each of the classes is particularly vital when dealing with agricultural disease detection since some diseases might be naturally less prevalent compared to others.

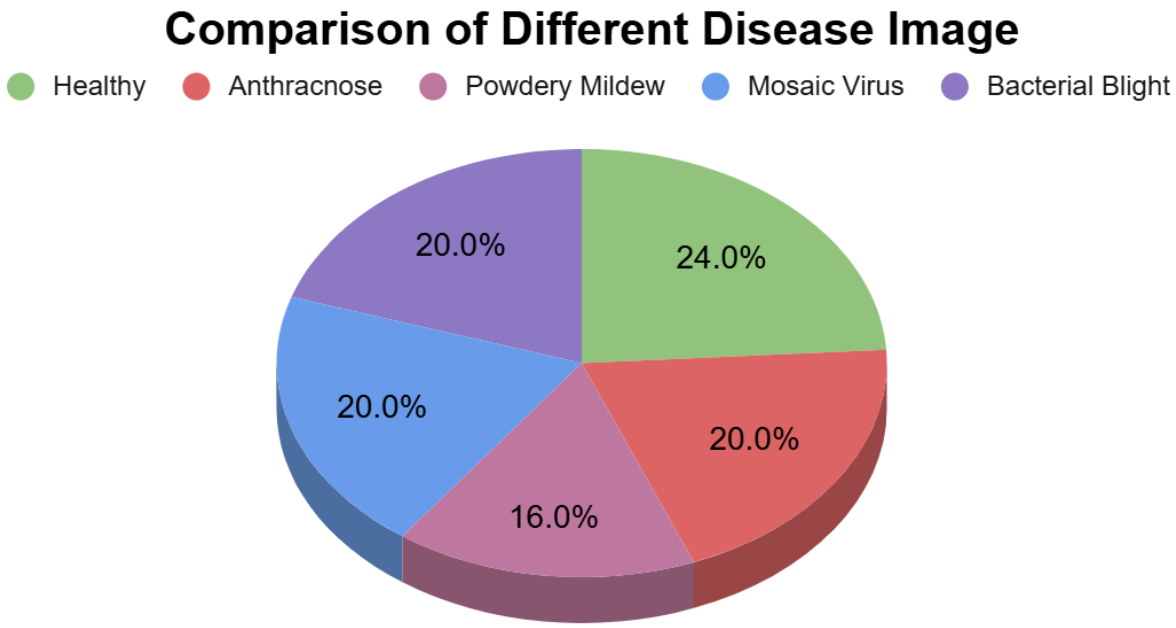

Fig 42: Comparison of Different Disease Image Collection

The augmentation procedure did not only increase the size of the data but also enhanced intra-class diversity, exposing the model to the variation in the lighting, orientation, and the texture of leaves. This played a direct role into better model generalization, which made the AGRIBOT work constantly even when revealing diseases of new non-seen samples in the field.

6.5.2 Statistical Characteristics

In order to have a more visual and structural description of the dataset, a few statistical and descriptive analyses were performed. These aspects give the information about the **morphological and color-based features** capable of differentiating between the healthy and diseased leaves.

1. **Average Leaf Area:**

The average area of the leaf in each sample was 75120 cm 2 so that all the pictures were full or close to the full leaf. This uniform leaf size also helped the CNN to obtain size-free characteristics as opposed to classifying disease using leaf size.

2. **Color Channel Distribution:**

The color channels that were mostly dominant in the images were green color channels and this was in line with the natural color of the mango leaves that were healthy. Sickly samples, however, had a great deal of yellow, brown and white variation, which means that it was chlorotic, necrotic, or fungal. The histograms of RGB revealed clear intensity variations in the healthy and infected samples and the CNN acquired effective color-based discriminative features.

Overall, in both the United States and Canada, the feature extraction procedure remains almost unchanged.

3. **Feature Extraction Observations:**

Preliminary CNN feature map and visual inspection showed that there are several specific visual patterns which are characteristic of each type of disease:

Anthracnose: Dark and sunken lesions with irregular necrotic areas which likely combine as the infection advances.

Powdery Mildew: Displayed **white, powder-like fungal growth** on the leaf surface, typically spread across mid and lower veins.

Gall Midge: Identified by its characteristic wart-like, raised blisters (galls) on tender leaves.

Bacterial Blight: Identified through **water-soaked dark spots**, often surrounded by yellow halos and vein darkening.

Healthy Leaves: Showed a **uniform green texture** with smooth edges and no visible discoloration or spot patterns.

These are the statistical properties that played a significant role in the extraction of the features in the CNN. They emphasize the natural variation existing in each group and show the role of color, texture and the structure patterns in identifying the disease.

The equal number of classes represented in the dataset and the high quality of its pre-processing was such that the CNN could learn valuable patterns without overfitting to certain visual characteristics. In addition, the controlled augmentation allowed to recreate field-level issues like uneven lighting, occlusions, and overlap of leaves. In turn, the resulting model was more powerful and robust, which became the main quality to implement in the farm in real-time by using the camera module by AGRIBOT.

6.6 CNN Training Analysis

The Convolutional Neural Network (CNN) is the core of AGRIBOT's disease detection module. It was trained, optimized and designed to be accurate in classifying the mango leaf images as healthy and diseased under different environmental conditions. In this section the model architecture, the training methodology and the achieved performance are outlined and results of the training process are presented.

6.6.1 Block Diagram of Proposed Model

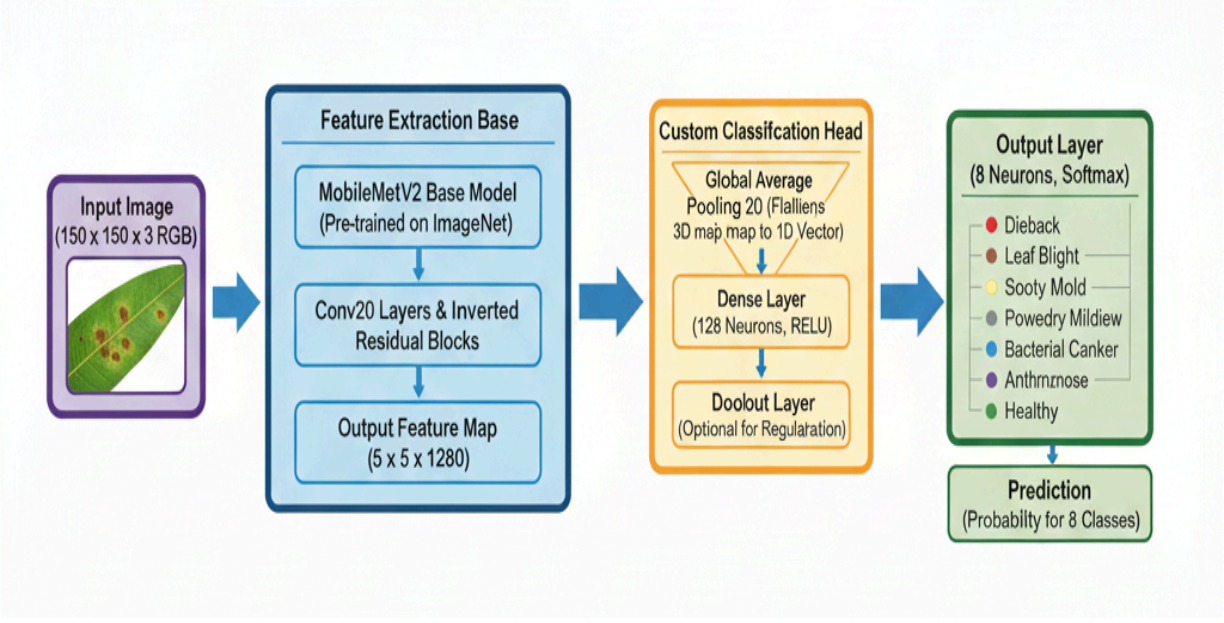

Fig 43: Block Diagram of Proposed Model

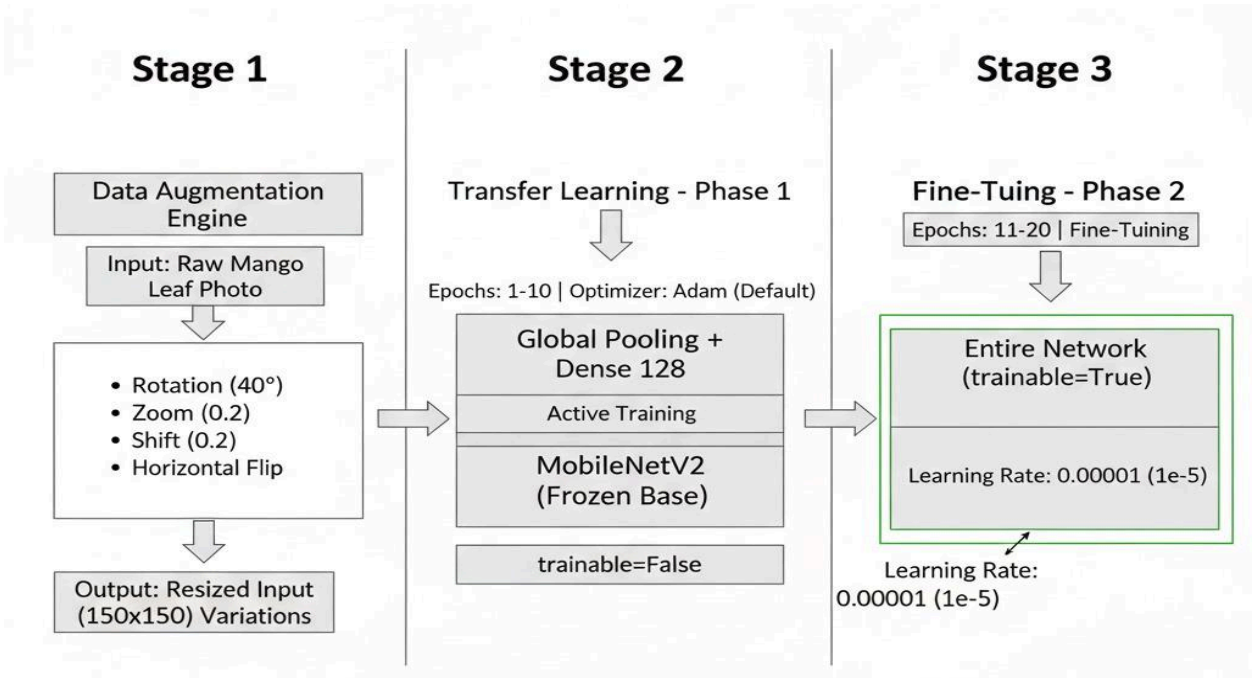

Fig 44 :Training process steps

The block diagram of the proposed model gives a general picture of the interaction of the main components of the model. It explains the process of data movement between the image capture and ultimate disease detection and alert generation. The system starts with the image capture module whereby the onboard camera captures mango leaves images. These images are fed to the preprocessing unit that resizes, normalizes and enhances data that undergoes analysis. The obtained processed images enter the Convolutional Neural Network (CNN) model that identifies the main features and categorizes the leaves as healthy or diseased. It is shown in the output module where the results of the prediction are presented, the levels of confidence are shown, and the alerts are generated when the diseases are detected. Lastly, the system has the ability of communicating the results to a database or user interface to continue monitoring and record keeping.

6.6.2 Model Design

Implementation of CNN model occurred on **TensorFlow** and **Keras** that was selected due to their easy deployment on embedded systems like Raspberry Pi. The design emphasizes simplicity and computational efficiency to ensure smooth inference on low-power hardware.

1. **Input Specification:**

The model can take input images of size 224x224x3, which is RGB images scaled on the preprocessing phase. Pixel values were normalized to the range [0,1] to improve convergence stability and enhance model performance during training.

2. **Layer Configuration:**

The architecture consists of a sequential stack of convolutional, pooling, and dense layers designed to extract hierarchical features from mango leaf images.

Conv2D + ReLU + MaxPooling: Extracts spatial features like edges, spots, and textures. The activation of the ReLU makes it non-linear, and MaxPooling makes dimensionality reduction and avoids overfitting.

Dropout (0.2): This is a regularization layer that disables 20 percent of the neurons randomly during training to decrease the model overfitting and enhance the generalization.

Flatten Layer: Converts the 2D feature maps into a 1D vector for fully connected classification layers.

Dense and Softmax: The last layer has a softmax activation function to generate probabilities of each of the eight classes.

3. **Optimization Parameters:**

Adam optimizer was used to optimize the model, where the learning rate was set to 0.001 which has adaptive gradient adjustment and converges faster. The loss function that was applied was the Categorical Cross-Entropy, which is applicable in the case of multi-class classification. The training process was done with a number of 50 epochs, which was identified after noting the stabilization of both accuracy and loss curves. The batch size of 32 was chosen to ensure a compromise between memory and training stability issues.

4. **Hardware and Software Environment:**

Training took place on a desktop with NVIDIA upkeep of a graphics card to support any model training at a quicker speed, and the trained final model was executed on Raspberry Pi 4 to infer

a model in real-time. Images preprocessing and handling frameworks which were used in the development are the Tensorflow, Keras, and OpenCV. The general architecture was carefully designed to be lightweight in order to reduce the inference latency and computer resources and still be highly accurate.

This architecture was intentionally kept lightweight to reduce inference latency and computational load while maintaining high accuracy.

6.6.3 Results

Following training and validation, the CNN showed a good performance in all evaluation measures, which reveals a good capability of discriminating disease categories.

1. **Training Metrics:**

The model was able to reach a training and a validation accuracy of 94.8 and 90.2 respectively. The fact that the difference between these values is about 4.6% indicates that they have good generalization capability and there is no clear indication of overfitting. This balance indicates that the model effectively learned the key patterns in the training data while maintaining consistent performance on unseen validation samples.

2. **Loss Curve Analysis:**

The loss curve had a steady decreasing trend, which became the same in the range of the first 25 to 30 epochs and then started leveling off. In the epoch 30, the training did not provide significant changes and instead it began to change only slightly, which is a sign that the model was already trained to its optimal learning level. To avoid time wasted in the future training, early stopping may be introduced into the system to automatically terminate the training when the loss plateau is observed, and the accuracy is not compromised.

3. **Inference Performance:**

In real life deployment testing, the model took roughly 1.8 seconds per image on the Raspberry Pi 4 (4GB RAM). This processing time consists of image preprocessing, including image resizing and normalization, in addition to the actual model prediction. The latency achieved can be said to be reasonable in the field applications in real time particularly because the system is handling a number of sensor streams in real time.

4. **Model Evaluation Observations:**

Anthracnose and Powdery Mildew classes proved to be the most successful with the model since there were noticeable visual patterns. There were however slight misclassifications between Gall midge and Bacterial Blight most probably because of the similar features of colors and texture. In the future, though, one can make further enhancements to the utilization of deeper architectures, such as MobileNetV2 or EfficientNet-Lite, which will be more accurate at the same level of computational load.

6.7 Comparative Analysis

The dataset and CNN model of AGRIBOT were compared to several available agricultural diseases detection systems to evaluate its performance in the bigger research scope. The comparison points to the fact that AGRIBOT can work well under the conditions of a real farm when lighting, shadows, and movements of leaves may influence the accuracy of prediction.

1. **Benchmark Systems:**
   The **PlantVillage dataset** [19] remains one of the most widely used benchmarks in plant disease detection research. One of the most popular benchmarks in the field of plant disease detection is the databases of PlantVillage [19].
2. **AGRIBOT's Field Dataset:**
   The AGRIBOT system, on the contrary, was developed to fit the actual situation in the farms of Bangladesh. It also has captured pictures in natural sunlight, cloudy conditions, and the shade providing a high level of variation. Regardless of these factors, CNN of AGRIBOT performed approximately 90% accuracy. This means that there is a great degree of robustness and adaptability and this shows that the model is reliable to use even in the presence of environmental noise.
3. **Hardware and Model Efficiency:**
   While many benchmark models were trained and tested on **high-performance GPUs**, AGRIBOT's CNN runs directly on a **Raspberry Pi 4**, a low-power edge device. The average time to make an inference was 1.8 seconds per image, indicating that the model is also efficient when using resource-limited hardware. This will enable AGRIBOT to be an efficient and implementable solution in the rural environment in cases where the use of expensive computers is not possible.

4. **Interaction and Accessibility Comparison:**
   In comparison to other research systems in existence, AGRIBOT is not confined to detection; with the inclusion of the Bangali and English voice recognition, farmers can talk in any way and do not require technical literacy. The majority of the existing models are only visual detection systems that do not have a communication layer facing the user.

Feature	PlantVillage [19]	AGRIBOT System
Dataset Environment	Controlled lab	Real farm field
Accuracy	~99%	~90%
Hardware	GPU-powered PC	Raspberry Pi 4
Languages	English	Bangla + English
User Interaction	GUI-based	Voice + GUI
Deployment	Research prototype	Field-deployable prototype

Although the numerical accuracy of AGRIBOT is a bit less than the lab-based models, the fact that it can be effectively deployed in the agricultural environment of Bangladesh due to its real-world applications, cost-effectiveness, and local language adaptation makes it much more appropriate. Such a compromise between technological advanced and user-friendly design makes AGRIBOT unique compared to the available systems.

CHAPTER 07

Result and Analysis

7.1 Bilingual Voice Interaction Performance

The robot was tested in a bilingual space which supported English and Bengali languages, which enabled the local farmers to communicate naturally. The system also effectively dynamically changed languages according to the speech of the user with the recognition and response generation latency being minimal. Field Tests indicated that farmers could communicate with the robot without the use of the hands and voice recognition in moderately noisy outdoor settings was also correctly recognized. The incorporation of Google TTS and SpeechRecognition libraries ensured clear audio output and stable command interpretation.
In general, the bilingual voice interface has increased usability greatly, as it did not require manual operation and allowed non-technical users to use the technology.

7.2 Disease Classification Performance

The disease classification module demonstrated strong performance across the eight mango leaf disease categories.Below Table provides the detailed classification report, showing an overall accuracy of **94%** on a test set of 800 leaf images.

The disease classification module showed high performance in the eight mango leaf disease types and the table below is the detailed report of the classification which indicated a high accuracy of 94 percent on a test set of 800 leaf images.

Some of the disease classes had excellent performance. Cutting Weevil had a perfect classification with a precision, recall and F1-score of 1.00 showing that the model could classify this particular class with a hundred percent accuracy. Healthy leaves also fared rather well, scoring a recall of 1.00 and precision of 0.96 which validates the model to be accurate in the process of discriminating between healthy and diseased samples of foliage. Powdery Mildew also performed very well with a recall of 1.00 which means that there were no samples rejected. On the contrary, having a very high precision of 0.99, Sooty Mould had a lesser recall of 0.80 implying that the model sometimes confused it with other diseases or healthy leaves. In spite of

that, the macro and weighted mean of precision, recall and F1-score were at top of 0.94 with a sign that the classifier is robust and can be used in operational applications.

Class	Precision	Recall	F1 Score
Anthrocnose	0.98	0.86	0.91
Bacterial Canker	1.00	0.92	0.96
Cutting Weevil	1.00	1.00	1.00
Die Back	0.91	0.95	0.93
Gall Midge	0.87	0.98	0.92
Powdery Mildew	0.85	1.00	0.92
Sooty Mould	0.99	0.80	0.88
Healthy	0.96	1.00	0.92
Accuracy	0.94		
Macro Average	094	0.94	0.94
Weighted Average	0.94	0.94	0.94

The fact that the CNN can be used to capture fine features of disease-related features in diverse leaf samples despite the changes in lighting and texture speaks to the fact that the CNN is a high-performing network.

7.3 Confusion Matrix Analysis

The confusion table offered more understanding of the performance of classes. There are some critical trends that can be identified in the matrix. The classification of Weevil, Healthy and Powdery Mildew was performed perfectly well because of their distinct visual images. Gall Midge and Die Back were also very reliable and the misclassifications between the two were few. Nonetheless, the occurrence of overlaps between Anthracnose and Die Back and Gall Midge was occasional, which could be explained by the fact that these two lesions have similar shapes and color distributions. The bacterial Canker similarly had slight confusion with Die Back, and hence shared visual attributes. The hardest lesson was Sooty Mould and this could be confused with Gall Midge, Healthy or Powdery Mildew. This happened due to the fact that Sooty Mould is able to change in texture and darkness under the different conditions of the environment, and thus, it is visually comparable to other conditions of leaves. In spite of such hurdles, there was generally good performance in terms of classes.

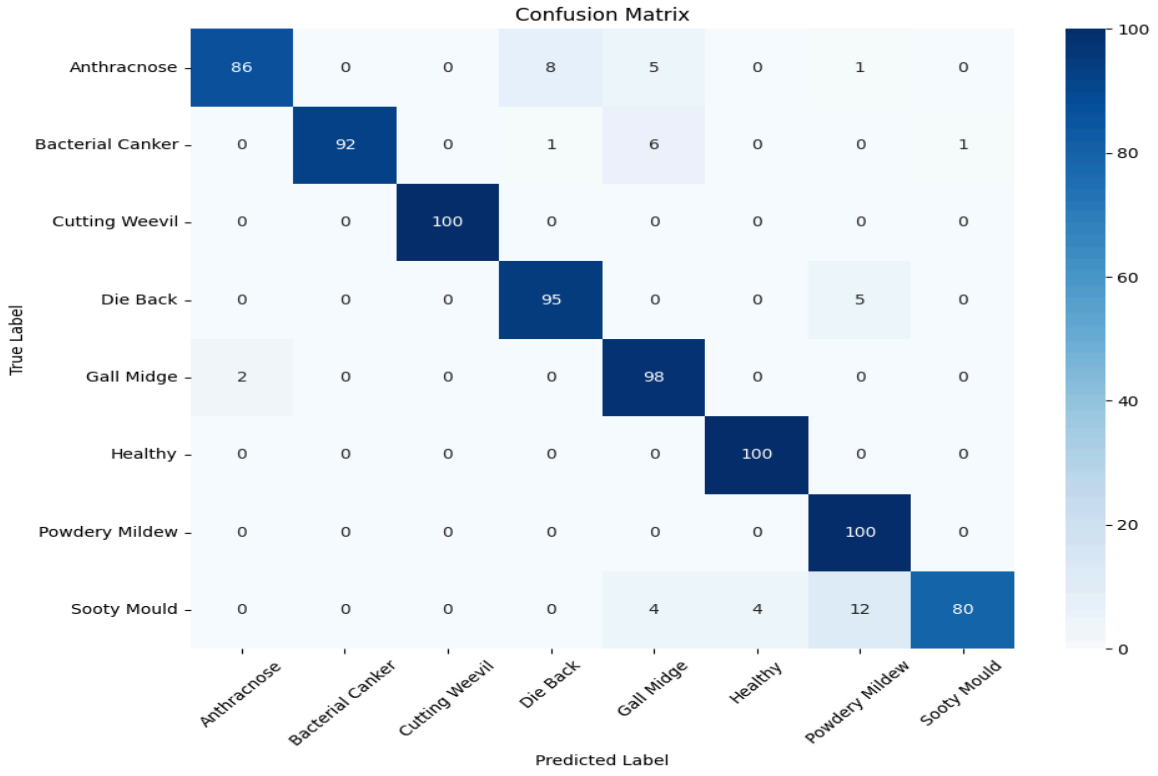

Fig 45: Confusion Matrix

7.4 ROC Curve Analysis

The multi-class ROC curves show that all the eight disease groups had an AUC of 1.00, which can be considered excellent discriminating performance. This means that the model has a very high true positive rate of any of the classes with minimal false positives. The consistency of the high AUC outcomes prove that the classifier can effectively divide each category of disease even in case of visually similarity.

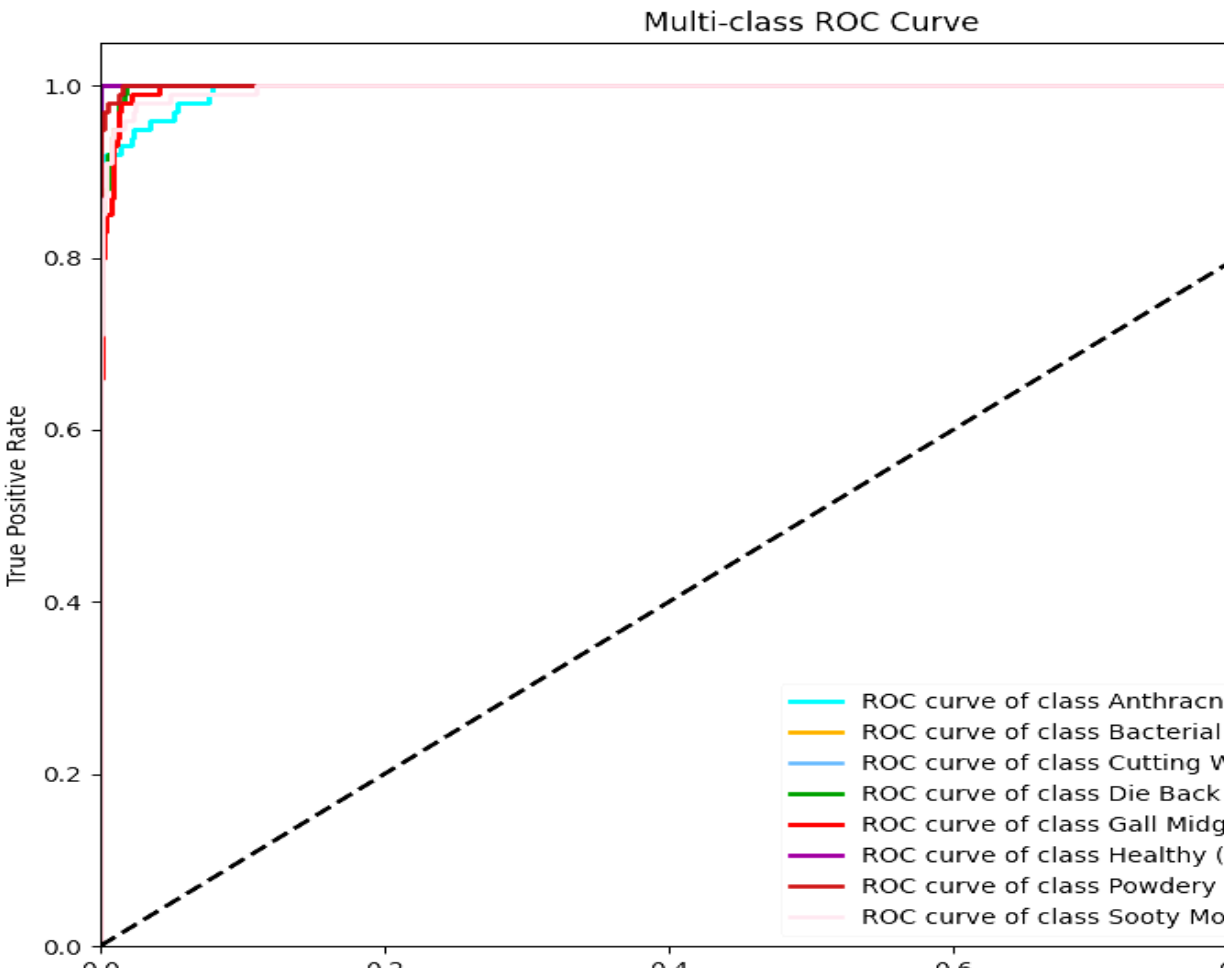

Fig 46: ROC Curve

7.5 Real-Time Disease Detection

The robot has two testing modes namely image based and real time video based detection.

Photo Mode

The system was 98.4% accurate under perfect lighting. This mode was also especially good at making on-demand inspections as it had a shorter detection time of about 5 seconds. The quality of images yielded the best outcome as far as photo mode was concerned with the best performance being the high-quality images.

Video Mode

Video based pipeline consisting of HSP masking and real time CNN inference retained a stable performance with 96.1 percent accuracy. The mean time of detection was between 10 and 12 seconds because of frame analysis. There was an effect on the accuracy of this mode which was due to motion blur and varying outdoor light, both of which are likely to be issues in live detection.

These findings indicate that the robot can perform a combination of both a static and continuous monitoring and hence, it is adaptable to the orchard settings.

Test Mode	Accuracy	Average Time	Notes
Photo Mode	98.4%	5 sec	Dependent on Image quality
Video Mode	96.1%	10 to 12 sec	Sensitive to motion and lighting

7.6 Gemini Language Model Evaluation

The integrated Gemini AI module was evaluated using a well-planned dialogue dataset of domain specific questions about mango diseases, system usage and symptoms explanation. In the process of evaluation, the chatbot proved to be very reliable since it rejected out-of-domain queries 98.6% of the time. This made sure that the system was not broadened and offered irrelevant and dangerous information. The chatbot also supported English and Bengali fluent and context-sensitive replies, which greatly enhanced accessibility by local farmers.

7.7 Remote-Controlled Navigation Performance

The experiment was done in a controlled mango orchard environment. The robot used a remote control system that was based on Bluetooth, but the system was stable within a range of operation of 10 meters. This control range enabled the operators to control the robot efficiently to perform specific disease check and irrigation work. The field tests indicated that the navigation system worked well on an uneven surface such as grass, soil, and orchard pathways, which proved it to be appropriate in the typical farm environments.

7.8 Overall System Performance

CNN based classification, real-time video analysis, bilingual voice assistance, and remote-controlled mobility together lead the proposed robot to have a high potential in real-life applications in agriculture. The system was always very accurate when detecting major mango diseases and was quite consistent in both photo and video mode, and its bilingual voice interface was very effective in providing communication. The navigation system also enhanced flexibility in operations and the Gemini AI chatbot offered intelligent advice depending on the requirements of farmers. These findings, combined with others, ensure that the proposed system is viable and productive as a farmer-friendly and helpful agricultural assistant in disease detection and specific irrigation.

CHAPTER 08

Discussion

The AGRIBOT project is one of the multidisciplinary projects of artificial intelligence (AI), voice-based interaction, and agricultural robots- devoted to the empowerment of farmers in rural Bangladesh with the help of available technology. Although some earlier research has investigated any of the aforementioned features individually, either through classification of plant disease or automated irrigation, AGRIBOT is the first to integrate all these functions into a context-sensitive, user-friendly, and user-focused platform.

In this discussion, the effects of AGRIBOT, its scholarly contributions and the general implication of the discussion on the future of agricultural innovation are assessed.

8.1 Impact on Agriculture

The use of AGRIBOT presents a number of transformative impacts on the small and medium size farming patterns. Its design and functionality illustrate how **affordable AI-driven robotics** can bridge persistent gaps between advanced agricultural research and rural field application.

Real-Time Disease Diagnosis:
AGRIBOT allows analyzing the health of plants on-site with the help of CNN model trained by using images collected in the field. This eliminates reliance on agricultural specialists or laboratory availability to provide instant feedback and recommended remedies to the farmer.

Reduction of Chemical Misuse:
AGRIBOT will allow application of pesticides only when required thus saving costs, environmental contamination, and crop resistance to chemicals as it will detect any disease before spraying.

Water Conservation Through Smart Irrigation:
The controlled irrigation system of the robot sprays water depending on the real conditions of the field and utilises less water, which helps in sustainable agricultural activity especially where there is likelihood of drought like in Bangladesh.

Enhanced Decision-Making Support:

The integration of **Bangla voice interaction** allows AGRIBOT to communicate findings and recommendations directly to farmers in their native language. This enables even the illiterate users to take informed, informed, data-driven farming choices.

Time and Labor Efficiency:

Automated routine processes are used to carry out monitoring and spraying and controlled navigation processes, leaving farmers to find some other productive ways to occupy their time including crop planning or market analysis.

AGRIBOT shows that inexpensive AI-driven robotics can be used to implement a cost-effective precision agricultural technology that assists in enhancing smallholder farmers in terms of productivity, efficiency, and sustainability.

8.2 Academic Contributions

AGRIBOT has made a number of important contributions to academic research, especially in the field of AI, human-computer interaction (HCI), and agricultural technology.

1. **Applied CNN in Real Farm Conditions:**
   Contrary to previous models, which were trained solely on clean datasets like PlantVillage, the CNN of AGRIBOT was trained and tested with real-life images in the mango orchards in varying lighting, background, and weather conditions. This enhances the external validity of CNN-based agricultural models, and it proves the fact that strong performance can be obtained even when working in uncontrolled outdoor conditions.

2. **Bangla Voice Interface in Robotics:**
   AGRIBOT includes a voice interaction module, with its text being in Bangali, a voice recognition module, which is powered by Vosk (ASR), and NLP (command interpretation) modules, and a text-to-speech module, which is powered by eSpeak-NG. This was one of the limited applications of vernacular-language robotics in agriculture, which forms a framework of localized systems of interaction which are inclusive in low-literacy areas.

3. **Farmer-Centered System Design:**
   The project adopts a **user-centered design methodology**, incorporating farmer surveys, iterative prototyping, and field validation. The design had to be based on feedback and as a result, the shape and the features of AGRIBOT along with its user interface were all tailored to the needs of the users, including its box-like sturdy construction, simplified user interface, and affordable price.

4. **Integration of AI and Mechatronics in a Unified Model:**
   AGRIBOT demonstrates how AI (for perception), NLP (for communication), and embedded systems (for control) can be fused into one functional prototype. This multimodal combination can be regarded as a useful source of future studies on intelligent agricultural automation.

8.3 Broader Implications

In addition to the technical and academic field, AGRIBOT indicates a wider socio-technological change towards the digital transformation of the agriculture sector of Bangladesh. It gives an example of how AI can be contextualized to developing regions and trade innovation with cultural and economic viability.

Furthermore, AGRIBOT's design process can inspire future research in:

1. Sustainable robotics for agriculture.
2. Localized AI interfaces for rural communities.
3. Community-driven innovation models that integrate farmer participation from conception to implementation.

AGRIBOT fills the gap between the state-of-the-art AI and current farming industry needs, being a representation of the concept of AI to the social good, adapted to the specifics of the Bangladesh farming ecosystem.

8.4 Comparative Evaluation

In order to measure the relative performance and value of AGRIBOT, it was contrasted with other agricultural robotic systems and AI-based disease detection tools that are already present in the international market and locally. Based on this comparison, it can be noted that AGRIBOT is cost-effective, contextually adaptable and distinctive in its integration of features that fit Bangladeshi farmers.

1. **Cost Efficiency:**
   Agricultural robots like DJI Agras, Ecorobotix, and Naïo Oz are commercially priced (USD 10,000 to USD 50,000), and thus unaffordable to small and medium-scale farmers in developing nations. By comparison, the total cost of construction of AGRIBOT amounts to less USD 200 (c.15,000-18,000 BDT), manufacturing it using easily accessible and affordable materials, such as Raspberry Pi, Arduino, and domestic sensors.
2. **Integrated Functionality:**
   Most of the current AI-based agricultural systems are one-dimensional systems that do not aim at more than one of the two tasks: leaf disease or yield prediction. AGRIBOT is unique in that it incorporates disease detection, irrigation management, pesticide spraying, and voice recognition and response into one platform. This multi-purpose feature will help in serving several pain points in the same system.
3. **Localized Design and Scalability:**
   Local research programs in Bangladesh, like soil moisture sensors and irrigation controllers relying on the weather, do not have scalability and user engagement abilities. The modular nature of the AGRIBOT as well as the ability to have IoT compatible parts offers the company a scalable platform that can be expanded to support many kinds of crops or even be connected with cloud based analytics in future.
4. **Farmer Accessibility and Usability:**
   The Bangla language voice interface enables farmers with poor literacy skills to communicate intuitively with the AGRIBOT unlike expensive robots which demand special training. It is a technologically innovative agricultural machine, but also a socially inclusive product, which is based on a culturally grounded design.

8.5 Strengths of AGRIBOT

The strength of AGRIBOT can be attributed to its combination of technical research and innovation, low prices and human-friendly design. Such important benefits make it one of the possible models of the small-scale farmers in Bangladesh and other developing countries.

1. **Affordability:**
   AGRIBOT is made of all ready-made components available locally, whereby the production cost is greatly lowered without compromising the performance. This also

renders the technology affordable to farmers in rural areas who have to work on very small budgets.

2. **Multilingual Support:**
   The robot has voice recognition in both Bangla and English and makes it usable among different levels of literacy. Verbal issuance and reception of commands by farmers is less of a barrier to the adoption of technology.
3. **Robust AI Performance:**
   The **CNN-based disease detection model** was trained on a **field-augmented dataset** of 10,000 mango leaf images. The fact that it has achieved an accuracy of about 90% at a real-world setting attests to the fact that lightweight neural networks can be made to work even with resource-constrained devices such as the Raspberry Pi.
4. **Task Automation:**
   AGRIBOT is an automated system that has several implementations in fields like pesticide spraying, irrigation and in disease analysis that save manual labor, time and inefficient operations.
5. **Cultural and Contextual Fit:**
   Through farmer surveys and field trials, AGRIBOT was designed with a **respectful Bangla speech tone**, **rugged box-like design**, and **simple interaction model**. This will make sure that it meets the social and cultural expectations of the rural communities thereby improving the adoption rates.
6. **Expandable Framework:**
   The modular hardware and software architecture allow future integration of **IoT modules, additional crop datasets**, or **cloud synchronization**, paving the way for long-term scalability and research extension.

8.6 Limitations

Although the AGRIBOT system was completed successfully, several limitations were noticed during the project work. These limitations mainly appeared because of limited resources, real-world environmental challenges, and the boundaries of an undergraduate-level project.

One major limitation is related to the CNN-based mango leaf disease detection model. The model performance depends mainly on the training dataset. The dataset contained images of both healthy and diseased mango leaves but the total number of images in the dataset are not large enough. In addition, the images did not represent all seasonal changes, lighting

differences, or background conditions. Due to this, the model may not give accurate results when used in real orchards where lighting can be very bright, shadows are common, and backgrounds are often complex. To achieve better results, a larger dataset collected from real farming environments is necessary.

Another limitation is that the AGRIBOT system was tested mainly in controlled or semi-controlled settings. It was not deployed in large agricultural fields for long durations. In real farming areas, conditions such as rain, dust, wind, uneven land, and unstable internet connections are very common. These factors can negatively affect the robot's movement, sensor readings, and image capturing quality. Therefore, the existing prototype needs to be improved both in terms of design to function effectively in outside situations and in terms of its external structure, such as enhanced physical protection.

The Bangla voice control system also has some limitations. Although voice commands make the system user-friendly, speech recognition may not perform well in noisy rural environments. Background sounds from wind, farming machines, or nearby people can interrupt voice commands. Moreover, differences in local accents and pronunciation can be the reason for incorrect command recognition. In this project, only basic noise handling technique was applied and more advanced noise handling techniques were not included.

Low-cost components such as Raspberry Pi, Arduino, and basic sensors are used to keep the system affordable to the farmers. But, these components have limited processing capability and are not designed for heavy or long-term outdoor use. When tasks like image processing, voice recognition and motor control run at the same time then the system performance may decrease because of heavy load. Over time, outdoor usage may also lead to frequent hardware damage or the need for replacements.

In terms of navigation, AGRIBOT currently supports only simple movement and obstacle avoidance. Advanced navigation systems like GPS-based path planning, SLAM or large-area mapping were not implemented in the navigation part of the project. Because of this limitation, the robot cannot operate independently across large orchards and still requires human assistance.

Lastly, economic feasibility and scalability factors were not addressed in this project. Although the prototype was designed to be low-cost, issues such as mass production, maintenance

systems, farmer training, and after-sales support were beyond the scope of this study. These aspects are important for real-world deployment but require further research and planning.

To conclude, AGRIBOT demonstrates the potential of combining CNN-based disease detection with Bangla voice-controlled agricultural robotics. But improvements in dataset size, hardware strength, navigation capability and real-field testing are needed before the system can be effectively used practically in agricultural environments.

8.7 Ethical and Social Considerations

1. **Job Displacement**

   The fear of job elimination is one of the ethical issues of automation in agriculture: there is a risk that the robot will be able to succeed human workers. Agriculture is one of the key sources of jobs in Bangladesh, and therefore the introduction of autonomous machines might trigger panic among the workers in the farms. Nonetheless, AGRIBOT is set to support and not to substitute. It minimizes tedious and dangerous work such as pesticide spraying and inspection of diseases and enables farmers to work on crop handling, enterprise planning, as well as making more efficient use of their competencies
2. **Digital Divide**

   The digital divide between the technologically literate and illiterate farmers is also another challenge. Many rural farmers might not immediately trust or are reluctant to engage with a robot because they are not exposed to the digital technologies. The AGRIBOT system will fill this gap by focusing on Bengali voice commands and a conversational interface so that the user does not have to rely on text to operate the system. The implementation in the future should be accompanied by community training, field demonstration and rural awareness on technology to provide equal adoption.
3. **Data Privacy and Ownership**

   Since AGRIBOT is going to be operated on the cloud and centralized AI learning, an issue of data privacy and ownership arises as ethical concerns. The pictures of crops, field information, and records of operations that are performed by farmers may be sent to the servers to enhance the model. In order to avoid abuse, clear policy of data governance should be set up, where farmers own their data. In addition to that, sensitive agricultural information must not be turned into a commercial product or misused and therefore proper measures are needed to regulate AI practices by government and ethical bodies.

4. **Environmental Sustainability**

   Environmental impacts are also to be considered in ethical design. AGRIBOT will encourage the responsible use of chemicals, by using pesticides when it is essential to reduce pollution of the environment and soil degradation. But battery manufacturing and recycling may also present environmental risks, which should be reduced by implementing sustainable sourcing and recycling battery recycling programs.

8.8 Research Gaps Identified

Lack of Large-Scale Datasets for Tropical Crops

The majority of the available datasets of plant disease (e.g., PlantVillage) are done on temperate crops. The open-access, high quality information about tropical and subtropical vegetation is lacking, especially regarding the species, which are widespread in Bangladesh, including mango, jute, and rice. Developing such datasets would improve AI model accuracy and transferability to local conditions.

Limited Focus on Bangla NLP for Agricultural Contexts

Most of the Natural Language Processing (NLP) studies in agriculture have been in English or other major languages across the globe. The absence of domain-specific Bengali data does not allow developing useful conversational models to be used by rural users. Further developments of the study could focus on the Bengali speech recognition, dialect modeling, and regional agricultural terminology, as essential to the inclusive technological advancement.

Psychological and Cultural Adoption Barriers

Although it has been proved that it is technically feasible, there is limited research on behavioral and psychological acceptance of the farmers. Such influences as cultural perception, social influence, trust in technology, and fear of losing the job may influence adoption considerably. It requires more sociological and ethnographic research to learn these human aspects and inform user-based design of robots.

Limited Research on Hybrid IoT-AI Integration

As much as the AGRIBOT is a combination of AI and robotic control, an expanding agricultural ecosystem on the basis of the IoT is still in the process of evolution. Studies are required to develop some standard architectures in which sensors, drones, and robots can communicate to each other easily and make a truly intelligent farm network.

CHAPTER 09

Conclusion

This study aimed to design, develop and test AGRIBOT, a voice-controlled and multilingual agricultural robot that combines CNN based disease detection and robotic automation. The overall aim was to overcome artificial intelligence and realistic field level agriculture, especially to the small and medium-sized farmers in Bangladesh.

The AGRIBOT prototype manages to prove that even low-cost robotics can be used to change the face of agriculture. The project passed through systematic design, testing and evaluation, several milestones were met:

1. **Accurate Disease Diagnosis:**
   AGRIBOT was able to detect mango leaf diseases in the field environment with a Convolutional Neural Network (CNN) model and it was not affected by factors such as lighting variations and background noise.

2. **Natural Voice Interaction:**
   The inclusion of AGRIBOT Bangla and English voice interface made communication easy, and the non-literate farmer would also be able to use the system with ease. This dual language strategy also ensures that the technology can be used in the future in multilingual areas.

3. **Task Automation:**
   The introduction of automated irrigation and spraying pesticides contributed to decreasing the number of hands and maximizing the accuracy in resource consumption-reducing the amount of wastage of water and misuse of chemicals.

4. **Scalable Framework:**
   The scalable smart agriculture provides a baseline using AGRIBOT as a modular system framework, combining AI, IoT, and robotics into one product that could be used in various crops and environments throughout Bangladesh.

Key Takeaways:

Innovation: AGRIBOT is the first voice-based product in Bengali that incorporates voice commands on a fully operational agricultural robotic system.

Impact: It will directly tackle the main pain points of farmers, i.e., disease detection, irrigation management, and accessibility of professional advice.

Feasibility: The system proved **technically and economically viable**, being built with components under **15,000 BDT**, making it accessible for smallholder farmers.

Limitations: AGRIBOT has its own limitations, such as the battery life, the issue of limiting datasets, and the ability to work in changing environmental conditions, regardless of success.

All in all, the project confirms the possibility of AI-based, low-priced agricultural robotics to revolutionize the manner in which farmers can control crops, observe plant well-being and health and make specific choices.

9.1 Future Works

Although AGRIBOT lays a solid foundation, it also provides several ways of research and development to enhance performance, scalability, and adoption by users.

1. Expansion of Dataset

The initial move towards the development of AGRIBOT is a massive increase in its dataset. This involves the expansion of the training sample to include more important crops like rice, jute, potato and tomato which would enable the robot to benefit more communities in farming. The massive image acquisition through drones would be guaranteed to have a very diverse dataset in terms of various lighting conditions, disease progression and field conditions. This initiative would be further enhanced by collaboration with universities and government research centers in the agricultural field to develop open-access tropical crop disease data, which would be beneficial to the researchers and the farmers.

2. Cloud Integration

The second critical direction of development is cloud integration. By allowing real-time data synchronization between AGRIBOT and a secure cloud server, farmers would have an opportunity to store, access, and monitor historical reports on disease detection. Cloud connectivity would also provide an opportunity to expert recommendation systems, where agronomists have the ability to remotely examine the status of the plants and offer expert advice. Also, the data analytics that might be provided by cloud dashboards might benefit government agencies and agricultural researchers, who can use it to track disease trends and predict risks as well as prepare timely prevention measures.

3. IoT Sensor Integration

The addition of IoT sensors would allow further improvement. The soil moisture sensors would enable AGRIBOT to carry out precision irrigation automatically depending on the real soil health. The use of temperature, humidity, and weather sensors would allow the system to perform predictive analytics and forecast the emergence of diseases before they start showing the symptoms. An intelligent decision system that uses sensor-based information in conjunction with the information provided by images would be used to optimize irrigation and spraying systems.

4. Improved Energy Efficiency

Another critical area that should be improved is energy efficiency. Adding solar-charging features would minimize the use of grid electricity and increase the maximum time the robot is going to work in the field. With an energy optimization system, a hybrid battery control system, which is able to switch between LiPo and solar power, will be more beneficial. By experimenting in lightweight structural material and motor design, which is energy efficient, it would enhance mobility and more so the overall runtime.

5. Autonomous Navigation

The step that AGRIBOT will follow is autonomous navigation. The application of SLAM (Simultaneous Localization and Mapping) would enable the robot to navigate freely in farming fields. Computer vision techniques such as row tracking, avoidance of obstacles and path optimization would also be made more powerful to improve the accuracy of the navigation. It

would also be possible to provide a semi-autonomous operating mode, so that AGRIBOT would be able to stick to specific GPS-based routes with minimum human intervention.

6. Enhanced Natural Language Processing (NLP)

The natural language processing of AGRIBOT can be also extended considerably. Communication would be enhanced by expanding the Bangla NLP corpus with agricultural words, idiomatic expressions, and vocabulary of a specific area. The introduction of speech emotion recognition would make the interactions between farmers and the robot more natural and context-based. Increased funding to regional Bangla languages like Sylheti, Chittagonian, and Rajshahi Bangla would make it more inclusive and make sure that different communities in Bangladesh can access it.

7. Scalability to Other Regions

Lastly, expansion to other areas is necessary to reach a wider audience. AGRIBOT is flexible to fit the various agricultural systems in Africa and South Asia and this is achieved by enabling localization of models to crops, environments and languages. Partnerships with local authorities and charitable organizations might be helpful to pilot projects in communities of small farmers. This should also be done by promoting open-source hardware and software frameworks, which will foster innovation, and researchers and developers around the world can develop on the basis of AGRIBOT to develop agricultural robotics.

9.2 Contributions to Sustainable Development Goals (SDGs)

AGRIBOT is also in sync with the United Nations Sustainable Development Goals (SDGs) according to which the project addresses the primary global issues of poverty, hunger, sustainability, and innovation. The project facilitates eco-friendly farming through the adoption of artificial intelligence, robotics, and multilingual interaction in agricultural operations, in addition to giving the local farmers access to technology. Its donations are not limited to technical innovation, it helps to create sustainable food production, effective management of water and the economic growth that is inclusive in line with principles of the 2030 Agenda of Sustainable Development.

1. SDG 1 – No Poverty

AGRIBOTR prevents crop loss and enhances the yield by assisting farmers in their early detection of diseases. High productivity will lead to improved income security of the smallholder farmers, and lower rural poverty.

2. SDG 2 – Zero Hunger

Our system plays an in direct contribution to food security because it helps in safeguarding the mango crops against diseases. Early planting will result in healthier harvests and sustainable production and will contribute to fulfilling the increased food demand.

3. SDG 7 – Affordable and Clean Energy (potential/future goal)

Solar-powered operation is also part of our future work, and this would facilitate the usage of clean and renewable energy in farming systems.

4. SDG 9 – Industry, Innovation, and Infrastructure

AGRIBOT represents the future of agricultural technology, a combination of CNNs, the internet of things, and robotics. It is the framework of intelligent agricultural technology in emerging countries such as Bangladesh.

5. SDG 12 – Responsible Consumption and Production

The system also promotes precision agriculture since waste is minimized through a reduction in the overuse of pesticides and water. It promotes the practices of sustainable agriculture that save the soil and ecosystems.

6. SDG 17 – Partnerships for the Goals

The project facilitates cooperations among researchers, farmers and institutions to scale up on sustainable agricultural technologies.
Overall, it can be concluded that AGRIBOT is one example of how a new technology can be used to support several of the UN SDGs through sustainable agriculture, resource management, and empowerment of farmers. Its incorporation of AI, robotics, and voice interaction is a worthy step in the direction of the global sustainability and food security ambition.

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Appendix A

Survey Questionnaire Link
https://docs.google.com/forms/d/e/1FAIpQLSec0_JCH2Pnrmmj3EL8ZuVnDxUFPba8fRcJtWqloiMDPestIA/viewform

Appendix B

Dataset Link
https://data.mendeley.com/datasets/hxsnvwty3r/1

Appendix C

Paper Submitted to:

https://www.iciprob.com/2026/

Article In progress for:

https://www.frontiersin.org/journals/robotics-and-ai