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# Leveraging Advanced Convolutional Neural Networks and IoT-Enabled Smart Sensors for Enhanced Tomato Disease Detection and Agricultural Management

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**ABSTRACT:**

Crop disease management is of great importance in the agriculture dominated economy of the developing nation Malawi. This ensures food availability in the region, which would otherwise be threatened. In this paper, most modern and advanced tactics for precise farming are presented, which are based on the fusion of advanced deep learning methods with IoT technologies. The authors propose a deep learning architecture based on Efficient Net convolutional group-wise transform EN-CGWT for effective feature extraction from crop images with limited annotated data and fewer computational resources. The smart agriculture management system utilizes various smart sensors, including soil moisture and humidity sensors, to capture real time field data, which can then guide optimal farm management.

Now we refer to the use of MobileNetV3 employed on the Plant Village dataset which allowed our tomato farming research to obtain an accuracy of 92.59%. When however farm images from the real life are employed, this might drop to about 9.2%, making generalization on various dataset remain a difficult task. This situation emphasizes the need for the structure of deep learning families that are adjustable in order to handle environmental diversity more efficiently.

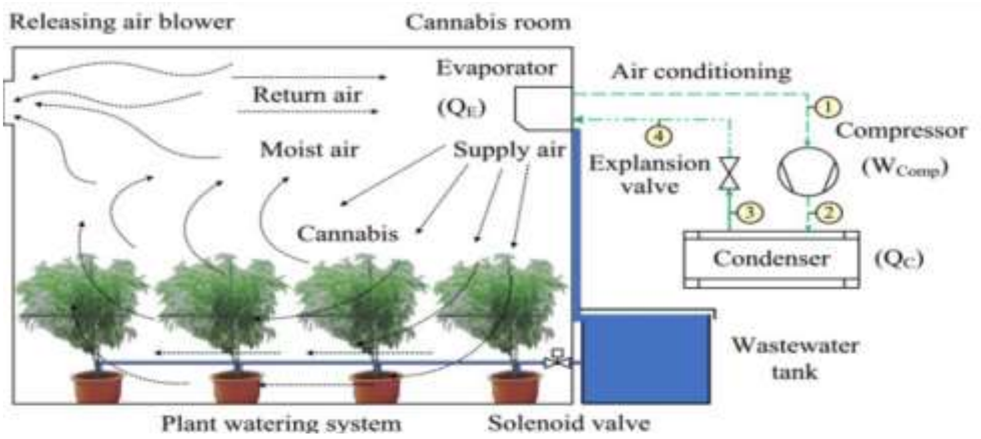
**KEYWORDS:** Crop Disease Management, Agriculture Economy, Food Security, Precision Farming, Deep Learning in Agriculture, IoT in Agriculture EfficientNet, Malawi, Food Security, Precision Farming, Deep Learning in Agriculture, Convolution Groupwise Transform (EN-CGWT), Feature Extraction, Smart Agriculture Management System.

## 1. INTRODUCTION:

Agriculture faces critical challenges due to crop diseases, which pose a serious threat to global food security by causing significant yield losses and economic strain. Timely and precise disease detection is essential for effective crop management, enabling farmers to proactively manage crop health, reduce losses, and optimize yields. However, traditional disease detection methods—based largely on human expertise and visual inspections—are often subjective, labor-intensive, and prone to error, making it difficult for farmers to respond effectively.

Recent advancements in artificial intelligence and machine learning, particularly in deep learning models like Convolutional Neural Networks (CNNs), offer promising solutions. CNNs can analyze visual symptoms in crop images with high accuracy and speed, automating the process of disease detection. The ENCGWT approach, for example, leverages EfficientNet CNNs for feature extraction, enhancing accuracy through deep neural networks, transfer learning, and techniques such as cross-channel attention in transformer-based models. These advancements have made automated disease detection more practical and accessible for agricultural applications.

In regions such as Malawi, where tomato farming is vital to both commercial and subsistence agriculture, farmers often lack the resources and expertise to identify and manage crop diseases. This research explores the use of MobileNetV3, a lightweight and efficient CNN architecture, tailored for resource-constrained environments like rural Malawi. By training the model on established datasets such as PlantVillage and validating it with local farm data, this study aims to provide an effective and scalable disease detection system. Ultimately, this approach can empower farmers with data-driven tools to monitor crop health in real-time, optimize resource management, and improve agricultural productivity.




The image is a diagram illustrating a sensory system deployment in the agriculture field, specifically for precision farming. The diagram shows various components and technologies used to monitor and manage agricultural activities through connected devices and cloud analytics.

The concept of Precision Agriculture is illustrated here as part of a larger ecosystem involving Cloud Analytics and Smart Farming. Cloud Analytics serves as a central component, interconnecting Precision Agriculture, Smart Farming, and Connected Agriculture by providing data processing and insights across these domains. Smart Farming links directly to Cloud Analytics, allowing data from various on-field activities to be analyzed and utilized effectively. Connected Agriculture also integrates with Cloud Analytics, enabling seamless communication between different components of the system. IEEE standards are prominently featured, providing standardized guidelines for data transfer, compatibility, and security across multiple components.

At the heart of the system is a Gateway that connects various sensors and communication technologies, enabling data flow from the field to analytical platforms. Communication Technologies, including Cellular, LoRaWAN, SigFox, eNode, and Backhaul, facilitate reliable data transmission between components, with clear distinctions made in the system for licensed and unlicensed spectrum usage. Various sensors are shown monitoring key environmental factors, such as water levels and plant conditions, and transmitting this information wirelessly. Plants are illustrated within the system, demonstrating how sensor data provides continuous monitoring to enhance precision in agricultural management. Overall, this image effectively captures the integration of diverse technologies, standards, and connectivity solutions to create a comprehensive precision farming system that enhances agricultural productivity and efficiency.

## 2. RELATED WORK:

The paper by Gutiérrez et al. (2013) introduces an automated irrigation system that uses a wireless sensor network (WSN) integrated with a GPRS module. This system is capable of monitoring and controlling irrigation processes remotely, which can significantly enhance agricultural efficiency and water conservation.

**2.1. Remote Monitoring and Control**: The integration of a GPRS module allows farmers to monitor soil moisture and other environmental factors remotely. This reduces the need for physical presence, saving time and labor costs.

**2.2.Water Conservation**: By automating the irrigation process based on soil moisture data, the system minimizes water waste and ensures optimal usage. This is especially beneficial in arid regions where water resources are scarce.

**2.3. Real-Time Data Collection**: The WSN collects real-time data on various environmental factors (like temperature and soil moisture). This immediate feedback enables more accurate irrigation, adjusting to changing conditions in real-time.

**2.4. Scalability and Flexibility**: The system's modular design makes it scalable and adaptable to different types of crops and field sizes. Additional sensors can be added as required, which makes it flexible for diverse agricultural needs.

**2.5. Energy Efficiency**: The system uses wireless communication, which reduces the need for extensive wiring and results in lower power consumption compared to traditional irrigation systems.

**2.6. Enhanced Communication Technologies:** Since GPRS is an older technology, you could explore using more advanced communication protocols, like LTE or even 5G, to improve speed and reliability.

**2.7. Integration with IoT and Machine Learning:** A modern system could utilize IoT and machine learning algorithms to predict weather patterns or plant water needs, further optimizing water usage and enhancing crop yield.

**2.8. Solar-Powered Systems:** Another angle could be designing a sustainable version of the system powered by solar panels, making it more suitable for remote areas with limited access to electricity.

**2.9. Cost-Effectiveness Analysis:** Conducting a comprehensive cost-benefit analysis to show the economic advantages of automated irrigation systems over traditional methods could appeal to policymakers and funders in the agriculture sector.

The paper by Agarwal, Gupta, and Biswas (2020) presents an efficient convolutional neural network (CNN) model designed to identify diseases in tomato crops. This approach leverages deep learning to aid in early disease detection, which can have significant implications for improving crop yield and quality.

**2.1.1. Accurate Disease Identification:** The CNN model developed in this study achieves high accuracy in identifying multiple tomato crop diseases. This is crucial for timely intervention and helps reduce the spread of diseases across plants.

**2.1.2. Efficiency in Computation:** The authors emphasize the model's efficiency, meaning it can operate effectively on limited computational resources. This advantage makes it more practical for real-world agricultural settings, especially in regions with limited access to high-performance computing.

**2.1.3. Reduction in Manual Labor and Costs:** The model automates the disease detection process, minimizing the need for manual inspection by experts, which can be labor-intensive and costly.

**2.1.4. Potential for Real-Time Implementation:** The model can be integrated with devices such as smartphones or embedded systems, enabling real-time disease detection on the field. This accessibility empowers farmers to take immediate action, reducing crop losses.

**2.1.5. Promotes Sustainable Farming Practices:** By allowing for precise disease identification, the model supports targeted application of pesticides, reducing unnecessary chemical use, which aligns with sustainable farming practices

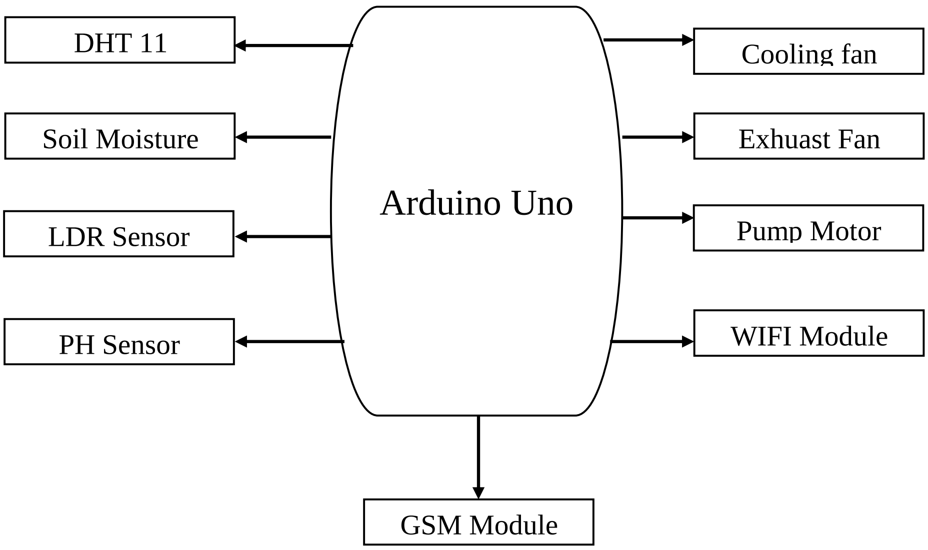
This paper can inspire new research by exploring ways to enhance or expand upon the CNN model for tomato disease identification:

**2.1.6. Broader Crop and Disease Coverage:** Building upon this CNN model to cover more crops and a wider range of diseases could make the model more versatile and widely applicable in agriculture.

**2.1.7. Transfer Learning and Model Generalization:** Developing a transfer learning approach to adapt the model for different plant species could improve generalization and decrease training time, making the model more practical for a variety of agricultural applications.

**2.1.8. Integration with Internet of Things (IoT) Devices:** The model could be embedded within IoT sensors or drones, enabling continuous disease monitoring

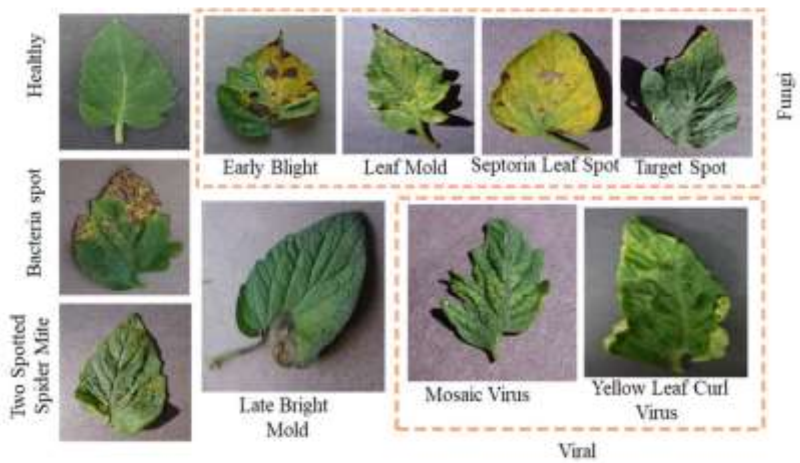
## 3. METHODOLOGY:




**A. Proposed system using IoT**

This IoT-based embedded smart sensor system for agriculture and farm management integrates various sensors, an Arduino Uno, and communication modules to optimize crop growth and farm productivity. The system includes sensors like DHT11 for temperature and humidity, a soil moisture sensor, an LDR (light-dependent resistor) sensor for light intensity, and a pH sensor to monitor soil acidity or alkalinity. The Arduino Uno serves as the central controller, processing sensor data and activating actuators, such as a cooling fan for temperature control, an exhaust fan for ventilation, and a pump motor for automated irrigation. Communication modules like GSM and Wi-Fi provide remote alerts and real-time data monitoring, enabling farmers to oversee their farms even from a distance. Each sensor sends data to the Arduino, where it's processed and compared to predefined thresholds set for optimal crop growth. For instance, if soil moisture drops below a critical level, the pump motor is triggered to irrigate the crops, while the cooling fan activates if the temperature exceeds a set limit. The LDR sensor assesses light intensity, allowing farmers to make decisions about artificial lighting or shade. The pH sensor helps manage soil health by monitoring its acidity, enabling the farmer to adjust soil treatment to maintain a healthy pH balance. This system automates decision-making, reducing manual intervention and labor costs, and logs data for trend analysis and long-term planning. Farmers receive alerts through SMS via the GSM module if any parameter exceeds its threshold, allowing for prompt action. Additionally, Wi-Fi connectivity enables wireless data transfer to cloud platforms for storage and analysis. This data can be accessed through a mobile app, offering farmers remote control of the system's actuators and real-time monitoring. The cloud integration allows historical data storage, trend analysis, and predictive analytics for better farm management decisions. The system's scalability enables the addition of extra sensors or actuators, adapting to various crop types, farm sizes, and environmental conditions. Energy efficiency is maintained as Arduino operates on low power, and the actuators are only triggered as needed. The system is designed for reliability, with error-checking to ensure sensors and actuators function accurately over time. Farmers can adjust threshold values based on crop-specific needs or seasonal changes, making the system highly customizable. By automating irrigation and environmental controls, the system promotes water conservation and energy efficiency. This IoT-based smart agriculture solution reduces water wastage, minimizes chemical usage by managing pH levels, and helps prevent crop damage with its early warning system.Through mobile access, farmers can adjust settings, view visualized data, and even provide feedback for system improvements. The user-friendly interface of the mobile app and cloud-based platform supports data visualization, making it easy for farmers to understand farm conditions at a glance. The data history also aids in compliance with agricultural standards and regulatory requirements. Predictive analysis, based on collected data trends, allows farmers to forecast crop yields and anticipate potential issues. The system offers operational scalability, allowing it to be scaled up for larger farms or more complex farming setups. This automation not only reduces labor costs but also enhances productivity by maintaining optimal growing conditions for crops. Designed to be cost-effective, the system uses affordable components like Arduino, making it accessible to small-scale farmers. The modular structure allows seamless integration with other smart farming systems or agricultural machinery, enabling a comprehensive farm management solution. Edge computing through Arduino reduces data transmission needs, saving bandwidth while ensuring quick responses. The system is field-tested to ensure reliability in diverse environmental conditions and is adaptable for different farming practices, crops, and regions. Maintenance alerts via the GSM module ensure that sensors and components are in top condition, enhancing the longevity and accuracy of the system. By fostering efficient resource use and providing real-time environmental data, this IoT solution supports sustainable farming practices. It enables farmers to make data-driven decisions, ensuring that water, energy, and soil resources are utilized optimally. The system's predictive capabilities help prepare for changing climate patterns, making farms more resilient to environmental shifts. Farmers can set customized notifications based on the priority of various parameters, receiving alerts only when necessary. Localization options allow adaptation to local conditions, enhancing the system's effectiveness across different climates. Security features ensure that data is protected during transmission, safeguarding farmer information and crop data. Overall, this smart agriculture system combines technology and farming expertise, providing farmers with a reliable, automated solution for efficient crop management and resource optimization. Through automated reports and mobile access, farmers can monitor, control, and manage their farms more effectively, reducing waste, improving productivity, and ensuring healthier crops.

**B. Pest detection and monitoring using CNN**




This research work describes a structured development of an efficient CNN and Transformer- based neural network model for crop disease detection. We employed three publicly available crop datasets capturing the different characteristics of crop species and disease conditions. The overall procedure was divided into the following stages: data collection, data preprocessing, model architecture design, training, and evaluation.

### *3.1. Data Collection*

We have employed the following three key datasets in training and validation:

**PlantVillage Dataset:** This dataset contains 54,305 images representing 38 crop disease classes across 14 plant species under various conditions. Each image is assigned to a unique crop disease class.

**Cassava Dataset:** This is a dataset gathered from the cassava disease classification competition. The dataset contains 26,337 images of cassava leaves with four classes of diseases and one healthy class, captured under real conditions in agricultural fields.

**Tomato Leaf Dataset**: An Overview The Tomato Leaf Dataset comprises images of tomato leaves in 11 classes belonging to ten various diseases and one healthy class which include those taken within the laboratory as well as those in fields.

These datasets have variations in conditions, such as imaging examples including light conditions, age, and nature of the severeness of disease that necessitate adaptability and robustness in the model.

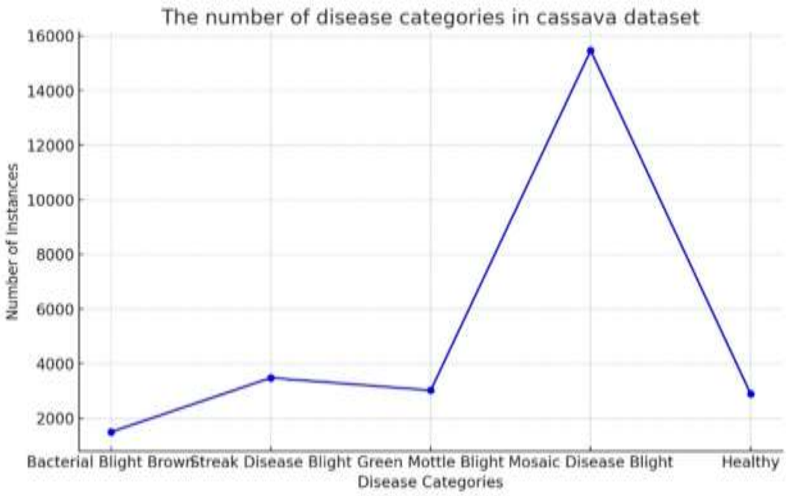
### *3.2. Preprocessing of Data*

To make the model generalizable to different types of quality in images as well as distribution in classes, we applied a set of data preprocessing procedures:

**Resize Images:** The dimensions of all images were resized to 256×256 pixels to make sure there is uniform input to the model.

**Data Augmentation**: Randomly rotate and flip and lighting adjustments added to better generalize the model, simulating variability in the real world of crop images.

**Class Balancing:** SMOTE was used on the cassava dataset that is class-imbalanced. SMOTE generates synthetic samples for the minority class by interpolating between neighborly data points, thus improving the ability of the model to learn all classes




### *3.3. Model Architecture Design*

The proposed model uses feature-extracting CNNs combined with Transformer layers to boost spatial attention. This combination of the two types of models is ultimately stronger in classification.

**EfficientNet Backbone**: We have adopted the EfficientNet as the CNN backbone, given that its architecture was optimized to provide both fairness in terms of accuracy and computational

efficiency. It effectively extracts complex features based on leaf texture and color variations from crop images.

**Group-Wise Transformer Layer**: To capture global contextual information and relationships between various regions within an image, we introduced group-wise Transformer layers on top of the CNN backbone. This structure enables the model to attend to spatially important regions to focus only on the key features, which thus enhances classification performance.

### *3.4. Model Training*

The model was trained on each dataset in turn and then was fine-tuned across datasets for improving its versatility. Key training parameters include:

**Loss Function:** Classification problems often require a cross-entropy loss function to learn class-specific features effectively.

**Optimizer:** The Adam optimizer was used in the training process along with scheduled learning rate decay for convergence.

**Batch Size and Epochs:** We used a batch size of 32 and trained up to 50 epochs with early stopping to prevent overfitting.

### *3.5. Model Evaluation*

We evaluated our models with multiple metrics across a different set of tests for each of the datasets used.

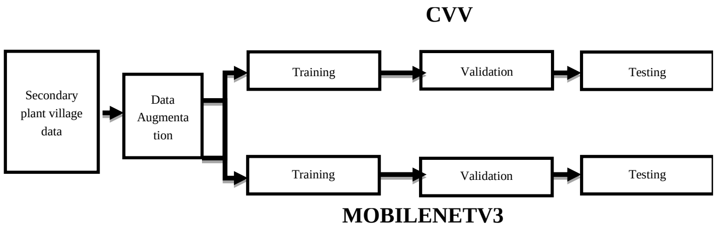
**Accuracy:** The overall correctness of the model in classifying the type of disease.

Precision, Recall, and F1-Score: These evaluate how well the model will predict diseased and healthy crops, especially in terms of minority classes.

**Confusion Matrix Analysis:** This gives a detailed view of the performance of the model on each class and highlights various areas that can be bettered.

Moreover, we validate our model in the form of cross-dataset validation with a test case so that we can understand the robustness of the model when handling realistic variations in crop diseases under different kinds of environmental conditions and imaging qualities.

**C. Tomato Leaf Disease Detection Using CNN and MobileNetV3**




The diagram outlines a machine learning process using Convolutional Neural Networks (CNNs) for image classification, likely for plant disease detection.

Here's a breakdown:

**A. Data Sources:**

**Primary Field Data:** This represents the main dataset collected from the field, containing images of plants with potential diseases.

**Secondary PlantVillage Data:** This is an additional dataset, likely from the PlantVillage project, providing more images for training and validation.

**B. Data Augmentation:**

This step involves applying various transformations to the images (e.g., rotation, flipping, cropping) to increase the dataset size and improve the model's robustness to variations in the input data.

**CNN Models:**

**Custom CNN:** The first model is a custom-built CNN, likely designed specifically for the task.

**MobileNetV3:** The second model is a pre-trained MobileNetV3, a lightweight CNN architecture suitable for mobile and embedded devices.

**C.Training, Validation, and Testing:**

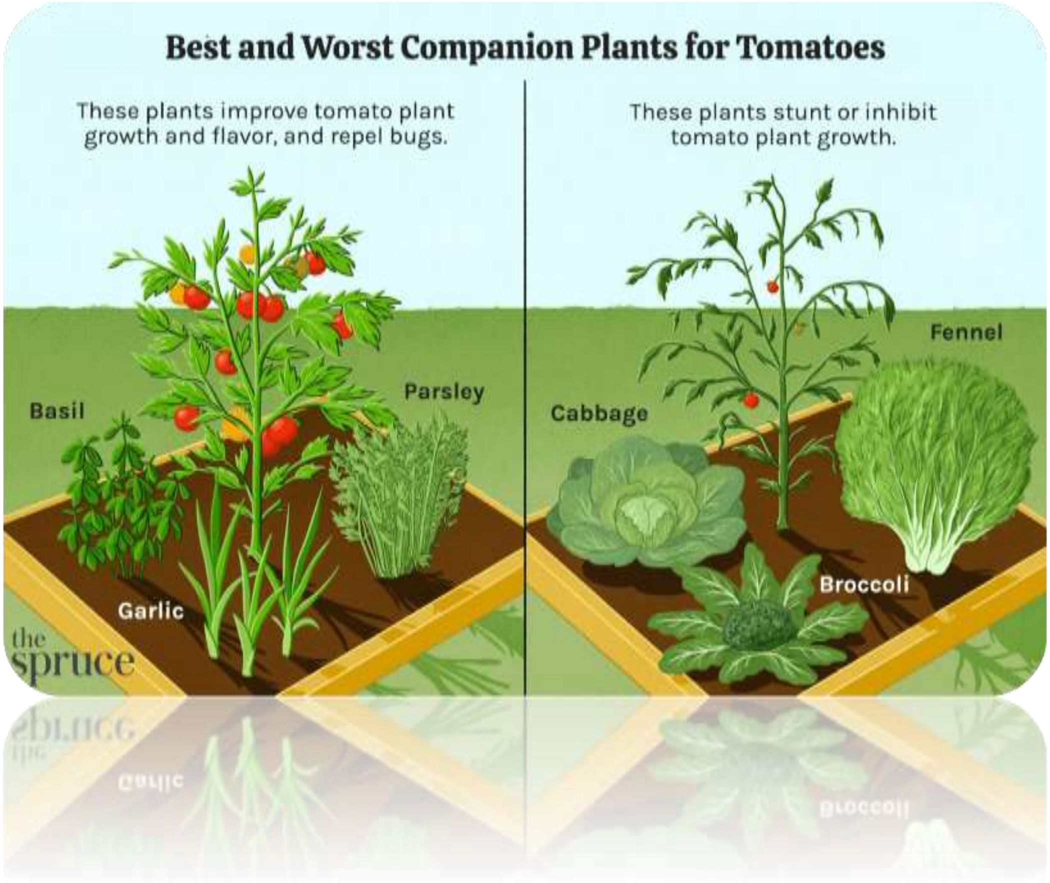
**Training:** Both CNN models are trained on the augmented dataset, learning to classify plant diseases based on the image features.

**Validation:** A separate validation set is used to monitor the model's performance during training and prevent overfitting.

**Testing:** Finally, the models are evaluated on a separate test set to assess their generalization capabilities on unseen data.

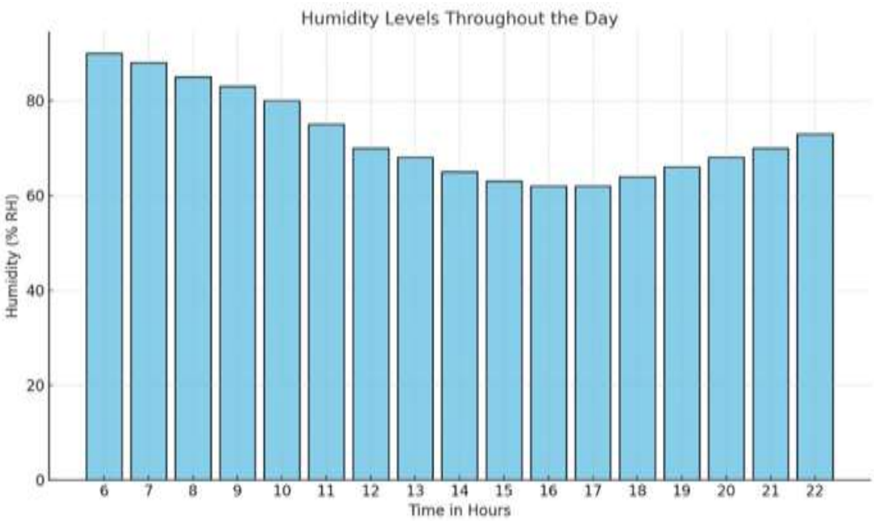
**Output:**

The trained models can then be used to classify new plant images and predict the presence and type of disease.

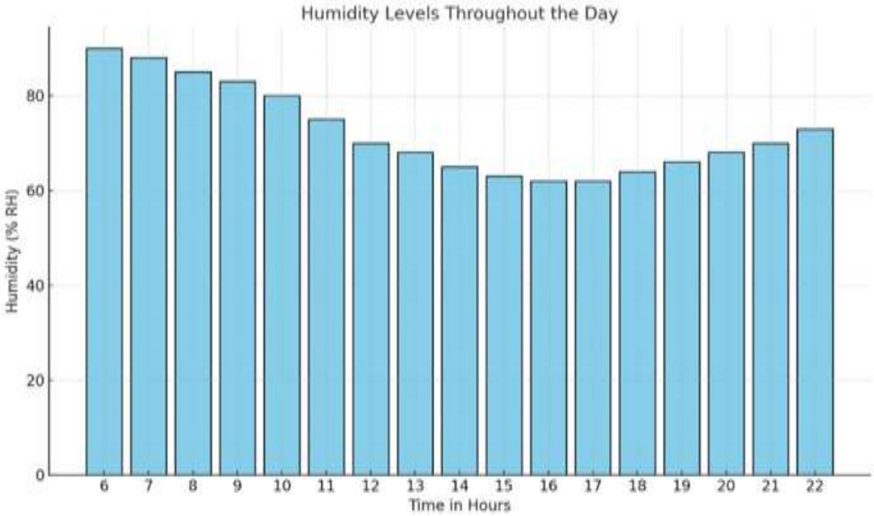



Companion planting is a strategic approach in gardening that can enhance the growth and resilience of tomato plants by pairing them with beneficial plants and avoiding those that hinder their development. Among beneficial companions, basil stands out for its ability to improve both the growth and flavor of tomatoes while naturally repelling insects, creating a healthier growing environment. Similarly, parsley not only enhances the flavor of tomatoes but also attracts beneficial insects that can help with pollination and pest control. Garlic is another valuable ally, as it repels common pests and may even help prevent certain plant diseases that affect tomatoes. However, not all plants make ideal companions for tomatoes. Cabbage, for example, competes aggressively for nutrients, potentially inhibiting tomato growth by depleting the soil. Broccoli poses a similar issue, consuming resources that tomatoes need and potentially stunting their growth if planted nearby. Fennel is particularly detrimental; it inhibits the growth of numerous plants, including tomatoes, and can significantly impact the vitality of the tomato crop. By carefully selecting companion plants, gardeners can optimize tomato health and yield while reducing the need for chemical interventions.

## 4. RESULTS:



The above graph shows temperature data collected from air and soil using sensor nodes over a period of time, specifically from 6:00 AM to 10:00 PM. The x-axis represents the time in hours, and the y-axis shows the temperature in degrees Celsius, ranging from 0 to 45 degrees.

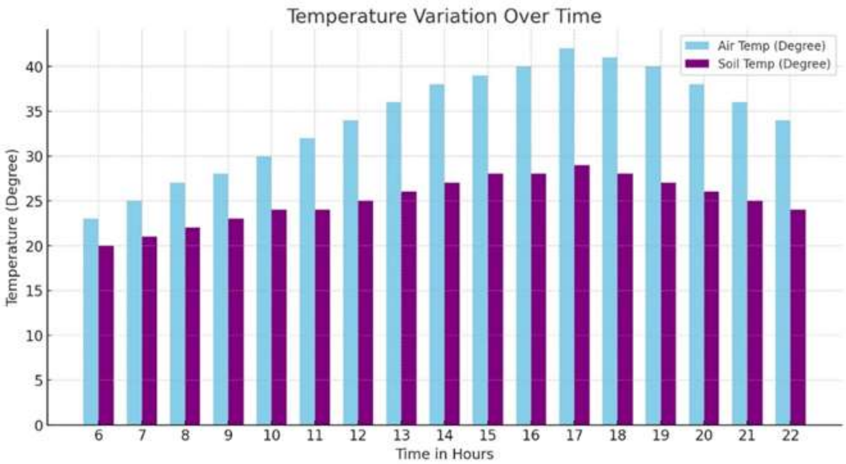



There are two lines on the graph:

- The light blue line represents the air temperature.
- The purple line represents the soil temperature.

Air Temperature:

- The air temperature starts at approximately 25 degrees Celsius at 6:00 AM.
- It gradually increases, reaching a peak of about 40 degrees Celsius around 2:00 PM.
- After this peak, the temperature starts to decrease, returning to about 25 degrees Celsius by 10:00 PM.




The above graph illustrates humidity levels measured over a period from 6:00 AM to 10:00 PM using sensory nodes. Here's a detailed breakdown of what the graph shows:

**1. Time Axis (x-axis):** The horizontal axis represents time in hours, ranging from 6:00 AM to 10:00 PM.

**2. Humidity Axis (y-axis):** The vertical axis represents humidity levels in percentage **relative humidity (%RH), ranging from 0% to 100%.**

**Data Points:**

- **Initial Humidity (6:00 AM):** The humidity starts at approximately 90%. This indicates a very high level of moisture in the air during the early morning.
- **Decreasing Trend:** From 6:00 AM to 1:00 PM, the humidity shows a gradual decrease. By 1:00 PM, it reaches its lowest point at around 60%. This drop is likely due to increasing temperatures as the day progresses, leading to a reduction in relative humidity.

- **Stabilization Period (1:00 PM - 5:00 PM):** Between 1:00 PM and 5:00 PM, the humidity levels remain relatively stable, hovering around the 60% mark. This period indicates consistent moisture levels in the air during the early afternoon.
- **Increasing Trend (After 5:00 PM**): After 5:00 PM, the humidity begins to rise again. By 10:00 PM, it climbs back up to approximately 80%. This rise in humidity in the evening can be attributed to cooling temperatures, which increase the relative humidity.

**Trends and Patterns:**

- **Daily Cycle:** The graph demonstrates a typical daily cycle of humidity. High in the morning, it decreases as the day warms up, stabilizes in the afternoon, and rises again as temperatures cool in the evening.
- **Environmental Insights:** The measurements from the sensory nodes provide critical information about the microclimate, which can be used for agricultural planning, understanding plant transpiration rates, and optimizing irrigation schedules.
- **Application in Agriculture**: Monitoring humidity is vital for crop management, as different crops require specific humidity levels for optimal growth. High humidity can promote disease, while low humidity can stress plants.

## 5. CONCLUSION:

Overall, the three studies infer that AI and IoT technologies for agricultural applications both hold promise and come with challenges. In fact, the first project demonstrates an actual time IoT farm monitoring system to optimize crop growth and productivity through continuous, real-time data acquisition and analysis of environmental information. Such an example illustrates how management of farms using datum can make resources much more efficient while increasing yields. The second project shows that a highly successful version of the EGWT model is developed over CNN-based and transformer-based approaches, resulting in better crop disease detection accuracy. The model therefore promises improved crop health management and an increase in food security.

However, this third study has a key limitation: AI models trained on controlled datasets, like that developed at Plant Village, tend to fail miserably when applied in real conditions in the field. The dramatic falloff in model performance on field data from Malawi makes clear the disconnect between laboratory training and real-world applicability, threatening to make the models more effective across environments.

This system, AI and IoT for agricultural management, has much promise; these technologies need to be fine-tuned to overcome practical obstacles. The real world introduces complexities that most models cannot handle well. More research and development must be conducted to fill this gap so that reliable AI can be comfortably deployed to realistically support and transform agriculture across the globe.

Further research into the adaptive models in different environments will be needed in order to achieve a full realization of the transformative power of AI and IoT in agriculture. Expanding the dataset to include as wide a variety of real-world scenarios as possible and developing algorithms that can self-adjust according to local variables related to climate, soil, or crop type will also be required. Further, accessing domain expertise by agronomists and utilizing high-end techniques such as transfer learning and domain adaptation can help improve the performance of models across regions. From this work, potential collaboration between technologists, agronomists, and farmers may eventually help them in building robust, holistic

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