ECO HARVESTING USING 5G TECHNOLOGY

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***Abstract*—Agriculture has always been in the bigger picture regarding human sustenance, yet traditional farming methods struggle to meet the increasing global demand for food production. With modern technologies, precision agriculture has emerged as a revolutionary approach to optimizing farming practices. Our project presents a cutting-edge system integrating 5G networks, drones, and deep learning techniques to enhance crop health monitoring and disease detection. By leveraging convolutional neural networks (CNNs) and the ResNet152v2 model, the system accurately identifies crop diseases from aerial imagery, enabling early intervention. Incorporating IoT sensors and real-time data transmission via 5G ensures seamless communication between components, allowing for precise and targeted pesticide application. This intelligent framework minimizes chemical overuse and enhances sustainability by reducing environmental impact. Furthermore, the proposed system enables large-scale monitoring with unprecedented accuracy, addressing limitations in traditional methods that rely on manual observation. By utilizing high-resolution drone imagery and AI-driven analysis, farmers can receive instant insights into crop conditions, enabling proactive decision-making. The integration of GPS-based mapping further ensures that treatments are applied only where necessary, reducing costs and preventing unnecessary chemical exposure to healthy crops. This holistic approach to smart farming improves yield and resource efficiency and aligns with global efforts to promote sustainable agricultural practices. By combining machine learning with high-speed connectivity, our project paves the way for a more intelligent, efficient agrarian system that maximizes productivity while promoting eco-friendly farming practices.**

***Index Terms*—Agriculture, 5G network, Crop Health, Internet of Things, Artificial Intelligence, GPS, Eco-farming.**

I. Introduction

On a large farm, a group of farmers and researchers stood together, looking up as drones flew over the fields. These drones were not ordinary ones; they had special cameras and sensors that could check the health of crops. Their mission was clear: to help farmers grow more food while using fewer chemicals and protecting the environment

Farming has always been challenging. Farmers often struggle with crop diseases, excessive pesticide use, and trying to get a good harvest without harming the land. Many times, they spray pesticides over the entire field, even if only a few plants are infected. This wastes chemicals, increases costs, and can damage the soil and surrounding environment. To solve these problems, the Eco Harvesting Using 5G Technology project was created. This project uses real-time data, artificial intelligence (AI), and high-speed 5G communication to make farming smarter and more efficient. As the drones moved across the farm, they took high-quality pictures of each plant. This information was then sent to an AI model called ResNet152V2, which quickly scanned the pictures and detected early signs of disease—even before a farmer could notice them. By identifying problems early, farmers could take action quickly and prevent diseases from spreading, which saved time, money, and crops.

Once the AI identified the unhealthy plants, their exact locations were marked using GPS technology. Instead of spraying chemicals across the entire field, a smart spraying system was activated. This system only sprayed pesticides on the affected plants, reducing the amount of chemicals used. This had two major benefits: it saved money and resources for farmers and protected the environment by preventing unnecessary chemicals from entering the air and water. By combining AI, drones, and 5G technology, this system made farming more accurate, efficient, and environmentally friendly. It helped farmers make better decisions, reduce waste, and increase their harvests. With real-time data and automated processes, they no longer had to rely on guesswork. They could see exactly which parts of the farm needed attention and take action immediately.

As the sun set over the fields, the farmers and researchers watched their technology in action, knowing they were creating a smarter and more sustainable future for agriculture. This system was not just about making farming easier—it was about helping the world produce more food in a way that is safe, efficient, and good for the planet.

II. OBJECTIVES

A. Key Objectives for Sustainable and Smart Agriculture

The objective of the Eco Harvesting Using 5G Technology project is to help farmers detect crop diseases at an early stage, allowing them to take action before the disease spreads and causes major damage. By using drones equipped with high-resolution cameras, the system continuously monitors crops and collects real-time data on their health. This data is analyzed using AI models like ResNet152V2, which can quickly identify signs of disease, even before they become visible to the human eye. Another key goal of this project is to reduce excessive pesticide use by ensuring that chemicals are applied only to affected plants rather than the entire field. Through GPS mapping and smart spraying technology, pesticides are precisely targeted, minimizing waste, lowering costs for farmers, and protecting the environment from harmful chemical exposure.

The project also aims to enhance efficiency in farming operations by utilizing 5G communication to process data instantly and provide farmers with quick, actionable insights. Instead of relying on manual inspection and guesswork, farmers can make informed decisions based on real-time data, leading to better crop management and higher yields. Additionally, resource conservation is a major focus, as the system optimizes the use of water, fertilizers, and pesticides, ensuring that farming remains sustainable and eco-friendly.

By integrating AI, drones, GPS, and 5G, the project strives to make farming more precise, cost-effective, and environmentally responsible. Ultimately, the goal is to empower farmers with advanced technology that not only increases productivity but also ensures that agriculture remains sustainable for future generations.

B. Objectives of the Eco Harvesting System Using 5G Technology

- **Early Detection of Crop Diseases** – The project uses **AI-powered image analysis** from drone-captured data to identify plant diseases at an early stage, allowing farmers to take quick action and prevent the spread of infections.
- **Precision-Based Resource Utilization** – By using **GPS-based targeted spraying**, the system ensures that pesticides and water are applied only to affected areas, reducing waste, lowering costs, and promoting environmentally friendly farming.

III. EXISTING SYSTEM

Agriculture has recently evolved with 5G-enabled IoT, as shown in the study "Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things," which uses WSNs to collect real-time data on soil and crop health, processed by machine learning models like SVM, Random Forest, and Naive Bayes to detect diseases, with SVM achieving the highest accuracy; the system includes a smartphone app for remote irrigation and pesticide control but faces limitations in large-scale use due to the lack of drones, connectivity issues, and slow response times, which the proposed "Eco Harvesting Using 5G Technology" aims to solve with drones, 5G, and smart spraying for a scalable, real-time solution [6].

Deep learning, particularly CNNs, has enhanced plant disease detection accuracy, with studies like Mohanty et al. (2016) and Ma et al. (2018) achieving over 93% accuracy, while transfer learning with models like VGG16 and ResNet50, along with data augmentation using GANs, addresses dataset limitations; recent advancements, such as hyperspectral imaging (Xie et al., 2021) with 95.1% accuracy for tomato disease detection and few-shot learning, further improve recognition with limited data [10].

The study "Transfer Learning-based Cotton Plant Disease Detection Using Resnet152V2 and Dense Neural Network Layers with Image Augmentation and Fine-tuning Techniques" uses Resnet152V2 with transfer learning and additional dense neural network layers to detect cotton plant diseases, achieving 98.36% accuracy through image augmentation and fine-tuning techniques [12].

The study "An Ensemble Transfer Learning-Based Deep Convolution Neural Network for the Detection and Classification of Diseased Cotton Leaves and Plants" uses a bagging ensemble technique combining five transfer learning models (InceptionV3, InceptionResNetV2, VGG16, MobileNet, and Xception) to classify diseased cotton leaves and plants, achieving 99.48% accuracy on binary datasets and 98.52% on multiclass datasets [8].

The research paper presents an AI-based hybrid CNN-LSTM model for rice crop disease prediction, aiming to enhance agricultural productivity by accurately identifying crop diseases. The model combines Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for sequential pattern analysis, improving prediction accuracy. The authors employ a large dataset of rice crop images, applying data augmentation techniques to enhance model performance. The hybrid model achieves superior accuracy compared to traditional CNN or LSTM models alone. The study highlights the potential of AI in precision agriculture by enabling early disease detection, reducing crop losses, and supporting farmers with timely interventions [4].

The [2] research paper presents a machine learning-based approach for identifying and classifying plant leaf diseases. The authors employ image processing techniques to enhance and extract key features from leaf images, followed by the application of Support Vector Machine (SVM) for classification. The process involves image acquisition, preprocessing, segmentation, feature extraction, and classification. The proposed model demonstrates high accuracy in detecting and categorizing leaf diseases, showcasing its potential for precision agriculture and assisting farmers in early disease detection.

This study [1] proposes a hybrid model combining 3D Convolutional Neural Networks (3D-CNN) and Long Short-Term Memory (LSTM) networks, optimized using the Whale Optimization Algorithm with Joint Search Mechanisms (JSWOA), achieving over 90% accuracy in predicting various maize leaf diseases on the Maize in field and KaraAgro AI maize datasets. This project introduces an LSTM-based CNN model for detecting apple diseases and pests using deep learning. By combining AlexNet, GoogleNet, and DenseNet201 with an ensemble majority voting approach, the system achieves high accuracy in classifying plant diseases from real-time images. The model enhances early detection, reducing reliance on manual inspection and supporting precision agriculture [11]. Transfer Learning and SE-ResNet152 Networks-Based for Small-Scale Unbalanced Fish Species Identification" This study introduces SE-ResNet152 with class-balanced focal loss for fish species identification on small-scale, unbalanced datasets. Using transfer learning, the model classifies fish images from body, head, and scale views, achieving 98.80%, 96.67%, and 91.25% accuracy on the Fish-Pak dataset. The approach outperforms traditional models, enhancing classification accuracy and robustness. It offers a reliable solution for automatic fish species recognition in aquatic research [13].

Plant Disease Detection Using Machine Learning This study presents a machine learning-based approach for plant disease detection using the Random Forest classifier. The model processes images of plant leaves, extracting features using Histogram of Oriented Gradients (HOG), Hu moments, and Haralick texture to classify them as diseased or healthy. The system was trained on a dataset of papaya leaves and achieved approximately 70% accuracy, with the potential for improvement using larger datasets and additional feature extraction techniques. This method provides an efficient and automated solution for early disease detection, aiding in agricultural sustainability [9].

IV. Precision Agriculture in Plant Disease Detection

Precision agriculture is revolutionizing farming by integrating advanced technologies to monitor and manage crops more efficiently. In plant disease detection, this approach is particularly transformative, allowing farmers to identify infections at an early stage, reduce crop losses, and minimize pesticide usage. Unlike traditional methods that rely on manual inspections, which are often time-consuming and prone to errors, precision agriculture leverages AI, machine learning, drones, and remote sensing to detect diseases before they spread widely.

Drones equipped with high-resolution cameras and multispectral sensors capture detailed images of crops, identifying subtle changes in leaf color, texture, and structure that indicate early signs of infection. These images are processed using AI-powered deep learning models, which analyze disease symptoms with high accuracy. Convolutional Neural Networks (CNNs) are commonly used for this purpose, enabling automated classification of different plant diseases without human intervention. Hyperspectral imaging further enhances early detection by capturing a broader spectrum of light, revealing biochemical changes in plants before visible symptoms appear.

Once a disease is detected, precision agriculture ensures that treatment is highly targeted. Rather than spraying entire fields with pesticides, farmers can use GPS-enabled systems to apply chemicals only to affected areas. Automated spraying drones, guided by AI-generated disease maps, reduce the overuse of chemicals, cutting costs and minimizing environmental impact. Variable Rate Technology (VRT) further optimizes pesticide and fertilizer application, adjusting dosage based on disease severity and location.

The integration of 5G and cloud computing has accelerated real-time disease detection and response. IoT sensors placed in fields continuously monitor plant health, soil conditions, and climate factors, transmitting live data to AI-based decision-making systems. With high-speed 5G connectivity, farmers receive instant notifications about potential infections, allowing them to take immediate action before the disease spreads. Cloud-based platforms store vast amounts of crop health data, improving predictive modeling and enabling precision farming on a large scale.

This technological synergy enhances agricultural productivity by minimizing crop losses and optimizing resource usage. Furthermore, the integration of machine learning algorithms with 5G and cloud computing enables automated pest control and efficient irrigation management, promoting sustainable farming practices.

V. Proposed System

The Eco Harvesting Using 5G Technology system is designed to enhance precision agriculture by integrating AI, drones, GPS, and 5G communication for efficient crop monitoring and disease detection. The system operates in multiple stages to ensure real-time data collection, analysis, and targeted intervention to improve crop health and sustainability.

Drones equipped with high-resolution cameras capture detailed images of crops, while AI-powered models like ResNet152V2 analyze these images to detect early signs of plant diseases. The AI system can identify infections before they are visible to the human eye, enabling early intervention to prevent disease spread. The affected plants are then marked using GPS technology, ensuring precise location tracking for targeted treatment.

Once disease-affected plants are identified, the system activates a smart spraying mechanism that applies pesticides only to the infected areas, minimizing chemical use and reducing environmental harm.

A. System architecture

5G connectivity ensures that all data is processed and transmitted in real-time, allowing farmers to receive instant updates and take quick action. Integrating automated processes and AI-driven insights eliminates guesswork, enabling farmers to make informed decisions about pesticide application, irrigation, and overall crop management.

By leveraging real-time data analytics and precision-based interventions, the proposed system improves farm productivity, reduces costs, and promotes sustainable farming practices. This approach helps farmers maximize yields while conserving resources, ensuring an environmentally friendly and cost-effective solution for modern agriculture.

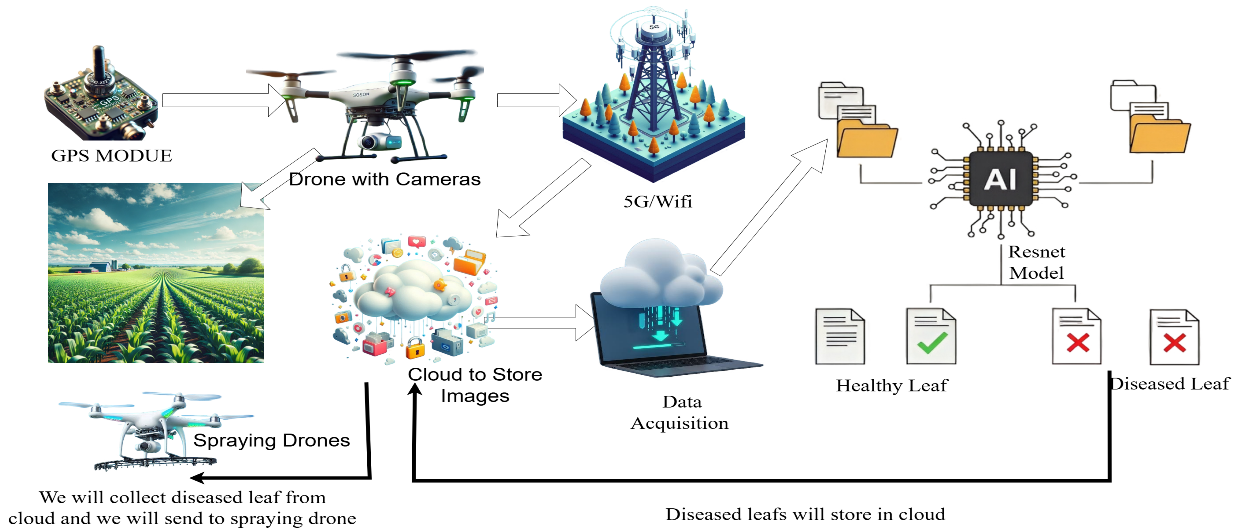

Fig. 1. This is a wide figure spanning both columns.

1) **GPS Module:** Provides precise geolocation data to navigate the drone accurately over agricultural fields, ensuring coverage of the entire plot.
2) **Drone:** An unmanned aerial vehicle that surveys fields, captures real-time data, and relays images and environmental details for analysis.
3) **Camera:** High-resolution imaging device attached to the drone, capturing detailed visuals of crop conditions for further processing.
4) **WiFi / 5G:** Enables ultra-fast and reliable communication between the drone and the cloud infrastructure, ensuring seamless data transfer.
5) **Cloud:** Acts as a central hub where captured images are uploaded, stored in EXIF format, and processed for analytical tasks.
6) **Data Acquisition:** Collects raw image and environmental data for analysis, forming the basis for detecting crop health and anomalies.
7) **Image Pre-Processing:** Improves the quality of images by removing noise, enhancing contrast, and preparing data for accurate segmentation.
8) **Image Segmentation:** Breaks down images into smaller regions to isolate and analyze plant leaves for disease detection and monitoring.
9) **Feature Extraction:** Identifies critical features such as leaf texture, color, and shape to distinguish healthy plants from diseased ones.
10) **AI Classification:** Uses machine learning models to classify plants based on extracted features into healthy or diseased categories.
11) **Healthy Leaf Plant:** Plants identified as healthy are left untouched, optimizing resources and focusing efforts on affected areas.
12) **Diseased Leaf Plant:** Detected as infected, these plants are flagged for intervention, prompting automated fertilizer or pesticide application.
13) **LIDAR Sensor:** Provides high-precision mapping and distance measurement to pinpoint the exact location of infected plants for targeted action.
14) **Automated Fertilizer Spraying:** Applies pesticides only to infected areas, reducing waste, promoting efficiency, and minimizing environmental impact.

B. Key Points

- AI-Powered Disease Detection and GPS-Based Targeting – Drones equipped with high-resolution cameras capture crop images, which are analyzed using AI models like ResNet152V2 to detect early signs of disease. Identified diseased plants are precisely marked using GPS technology for targeted intervention.
- Smart Spraying Mechanism with 5G Connectivity – Instead of spraying pesticides across the entire field, an automated smart spraying system applies chemicals only to affected plants, reducing waste and environmental impact. 5G communication enables real-time data processing, ensuring quick decision-making and efficient farm management.

C. Model Selection

For this research, we use the ResNet-152V2 model [3]. Deep neural networks with hundreds of layers initially show promise in recognizing images, but as they get deeper, they often face challenges like vanishing gradients and unstable training. This raised a fundamental question in deep learning: Is there a limit to how deep neural networks can go? ResNet (Residual Networks) revolutionized the field by introducing residual connections, which allow information to skip layers, addressing these issues and enabling effective training of very deep networks. Building on this, ResNet-152V2 improved the architecture further by introducing pre-activation residual blocks, where batch normalization is applied before convolutions rather than after. This small but powerful change led to smoother gradient flow, faster convergence, and more stable training, making deep networks even more efficient.

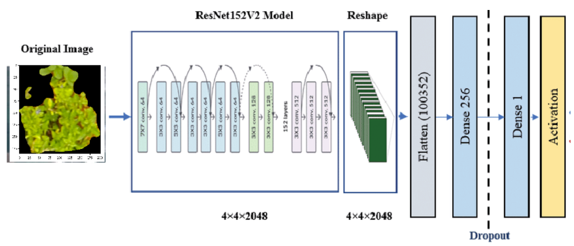

Fig. 2. Resnet152v2 model

With 152 layers, ResNet-152V2 is designed to extract hierarchical features from images, detecting everything from basic edges to complex objects, thanks to its skip connections. Its impact extends beyond theory, finding applications in medical imaging (disease detection in X-rays and MRIs), autonomous vehicles (pedestrian and traffic sign recognition), and satellite imagery (land cover analysis and climate monitoring). By refining how deep learning models process information, ResNet-152V2 has set a new standard, pushing the boundaries of artificial intelligence and paving the way for future breakthroughs.

The fundamental formula that defines the Residual Learning concept in ResNet is:

$$y = F(x, W) + x \tag{1}$$

Where:

- x = Input to the residual block
- W = Weights of the convolutional layers
- $F(x, W)$ = Transformation (convolution, batch normalization, activation)
  applied to x
- y = Output of the residual block

$$y = x + \mathcal{H}(\text{BN}(\text{ReLU}(Wx))) \tag{2}$$

Where:

- **BN** = Batch Normalization
- **ReLU** = Activation function (Rectified Linear Unit)
- **W** = Convolution weights
- $\mathcal{H}(\cdot)$ = Non-linear transformation

Support Vector Machine (SVM) is a supervised learning algorithm widely used for plant disease classification due to its ability to handle high-dimensional data and deliver accurate results even with small datasets. It identifies an optimal hyperplane that maximizes the margin between classes, ensuring precise classification. SVM employs kernel functions such as linear, polynomial, and radial basis function (RBF) to handle nonlinear separations, making it effective for analyzing plant disease symptoms.

We selected SVM for plant disease detection because of its efficiency in handling limited datasets, robustness against overfitting, and strong performance in distinguishing disease patterns [5]. Unlike deep learning models, which require large amounts of labeled data, SVM can work effectively with fewer samples while maintaining high accuracy. Additionally, its reliance on well-defined mathematical principles ensures consistent results across different plant species and disease types.

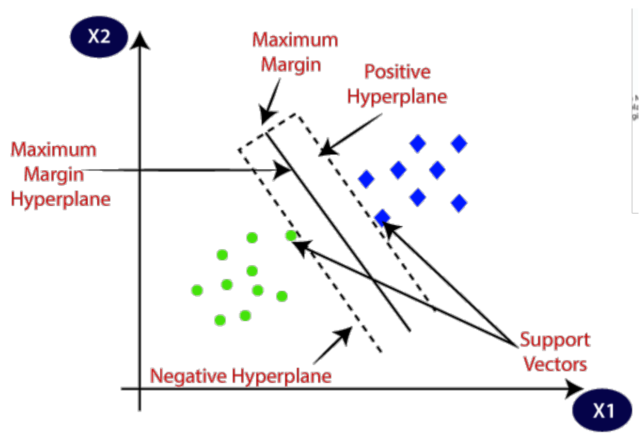

Fig. 3. Support Vector Machine (SVM) model.

Given a set of training samples (x_i, y_i) where x_i represents feature vectors and y_i represents class labels ($y_i \in \{-1, 1\}$), SVM finds the optimal hyperplane defined as:

$$f(x) = w^T x + b \tag{3}$$

where w is the weight vector and b is the bias. The objective is to maximize the margin while satisfying the constraint:

$$y_i(w^T x_i + b) \geq 1, \quad \forall i \tag{4}$$

To handle non-linearly separable data, a soft-margin SVM introduces a slack variable ξ_i, leading to the optimization problem:

$$\min_{w,b,\xi} \frac{1}{2}||w||^2 + C \sum_{i=1}^{n} \xi_i \tag{5}$$

where C is a regularization parameter controlling the trade-off between maximizing the margin and minimizing classification errors.

For non-linear classification, SVM uses a kernel function $K(x_i, x_j)$ to map data into a higher-dimensional space:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{6}$$

Deep learning has significantly improved plant disease detection, with Convolutional Neural Networks (CNNs) excelling in feature extraction and Long Short-Term Memory (LSTM) networks handling sequential dependencies. A hybrid

CNN-LSTM model combines these strengths, enabling accurate and efficient disease classification. The CNN component extracts spatial features from plant leaf images, while the LSTM processes temporal or sequential dependencies, making it ideal for analyzing plant disease progression over time.

CNNs are powerful in extracting spatial features from images by applying convolutional filters, pooling operations, and fully connected layers. However, CNNs lack the ability to capture sequential relationships in time-series or multi-frame data. LSTM networks, a type of recurrent neural network (RNN), are designed to handle long-term dependencies, making them effective for modeling temporal patterns in plant disease detection. Combining CNN and LSTM enhances classification performance, leveraging CNN's spatial feature extraction and LSTM's sequential learning capabilities [7].

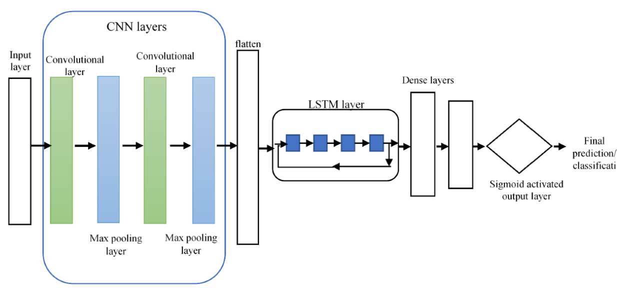

Fig. 4. CNN and Lstm model.

D. CNN Feature Extraction

Given an input image I of size $(H \times W \times C)$, where H, W, and C are the height, width, and number of channels, respectively, CNN applies convolutional filters W_f to extract feature maps:

$$F_k = \sigma(W_f * I + b_f) \tag{7}$$

where $*$ denotes the convolution operation, b_f is the bias term, and σ is the activation function (e.g., ReLU). Pooling layers then downsample the feature maps to reduce dimensionality.

The extracted feature vector from CNN, denoted as X_t, is then processed by an LSTM network, where each LSTM cell updates its hidden state as follows:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{8}$$

$$h_t = o_t \tanh(C_t) \tag{9}$$

where C_t is the cell state, h_t is the hidden state, and f_t, i_t, and o_t are the forget, input, and output gates, respectively.

The final LSTM output h_T is passed through a fully connected layer with a softmax activation function to predict disease classes:

$$y = \text{softmax}(W_y h_T + b_y) \tag{10}$$

where W_y and b_y are the weights and bias for the classification layer.

The hybrid CNN-LSTM model enhances plant disease detection by combining CNN's feature extraction with LSTM's ability to capture sequential dependencies. This approach improves accuracy, especially in time-series or multi-frame datasets, making it an effective deep learning technique for precision agriculture.

VI. Model Performance

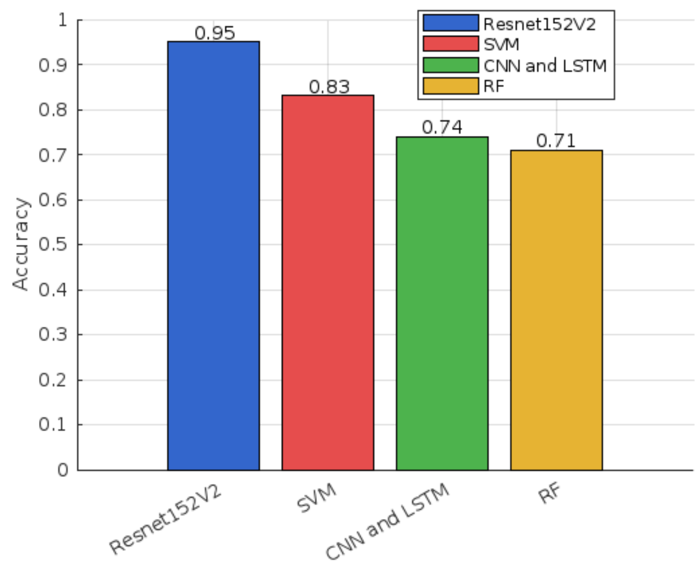

Fig. 5. Accuracy of Models.

Figure 5 compares the accuracy of four models: Resnet152V2, Support Vector Machine (SVM), CNN and LSTM-Hybrid, and Random Forest (RF). Resnet152V2 achieves the highest accuracy at 0.95, followed by SVM at 0.83. The CNN and LSTM-Hybrid model has an accuracy of 0.74, while the Random Forest model performs the lowest at 0.71. This indicates that Resnet152V2 outperforms the other models significantly in terms of accuracy.

Figure 6 compares the precision of four models: Resnet152V2, Support Vector Machine (SVM), CNN and LSTM-Hybrid, and Random Forest (RF). Resnet152V2 achieves the highest precision, nearing 0.95, indicating its strong ability to minimize false positives. SVM follows with a precision of around 0.82, showing a balanced performance. The CNN and LSTM-Hybrid model achieves a moderate precision of approximately 0.72, while Random Forest performs the lowest at around 0.69, highlighting its relatively weaker capability in accurately identifying positive cases.

Figure 7 compares the recall of four models: Resnet152V2, Support Vector Machine (SVM), CNN and LSTM-Hybrid, and Random Forest (RF). Resnet152V2 achieves the highest recall, nearing 0.96, indicating its superior ability to correctly identify positive cases. SVM follows with a recall of around 0.84, demonstrating strong performance. The CNN and LSTM-Hybrid model has a moderate recall of approximately 0.75, while Random Forest performs the lowest at around 0.71,

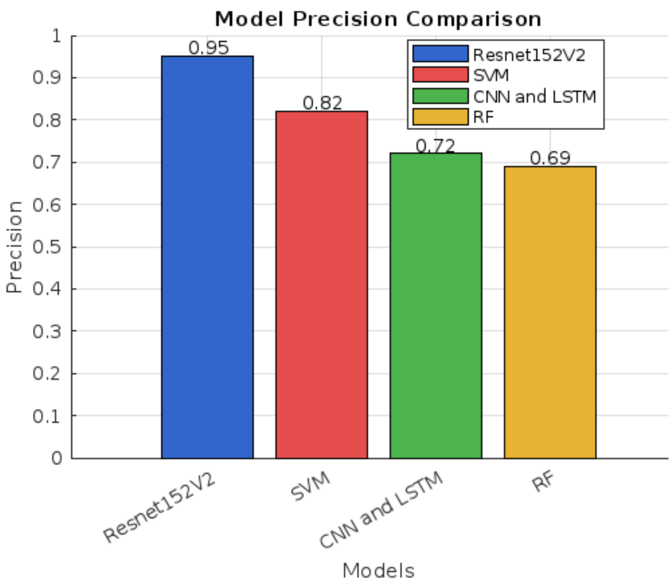

Fig. 6. Precision of Model.

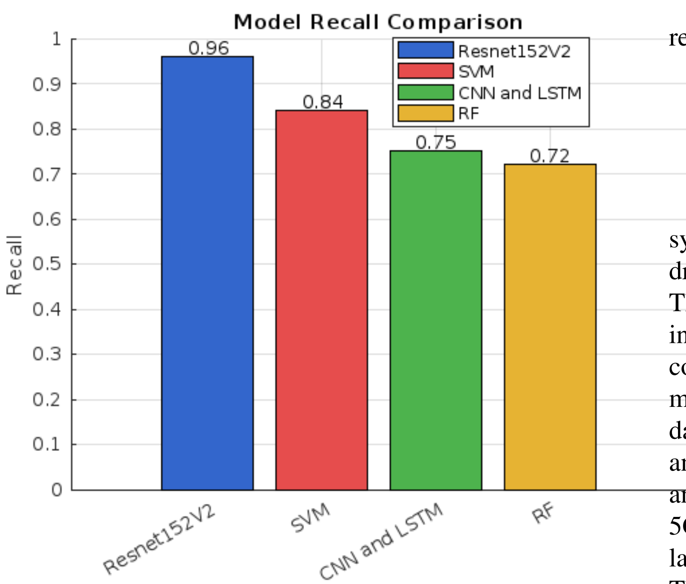

Fig. 7. Recall of Model.

highlighting its weaker capability in capturing all relevant positive instances.

Figure 8 compares the F1-scores of four models: Resnet152V2, Support Vector Machine (SVM), CNN and LSTM-Hybrid, and Random Forest (RF). Resnet152V2 achieves the highest F1-score, nearing 0.95, indicating its superior balance between precision and recall. SVM follows with an F1-score of around 0.83, showcasing strong performance. The CNN and LSTM-Hybrid model scores approximately 0.74, reflecting moderate effectiveness. Random Forest has the lowest F1-score, around 0.71, highlighting its weaker overall performance in maintaining a balance between precision and

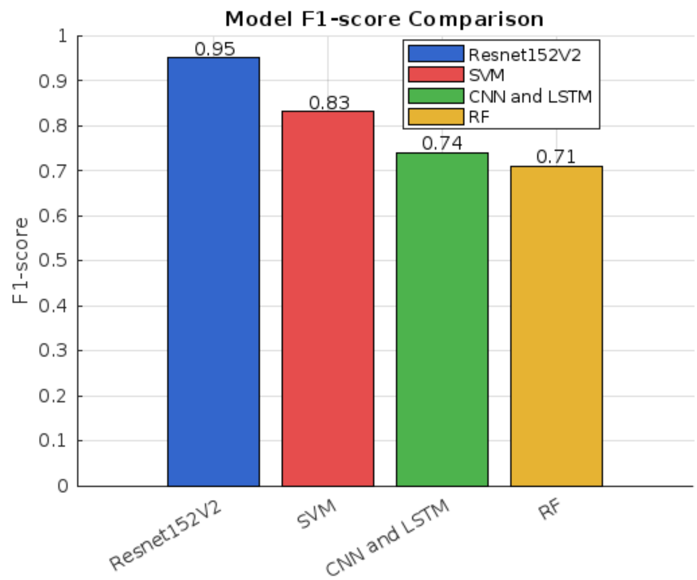

Fig. 8. F1-Score of Model.

recall.

VII. Conclusion

The proposed Eco Harvesting Using 5G Technology sys- tem demonstrates the effectiveness of integrating AI, drones, GPS, and 5G communication for precision agriculture. The system enhances plant disease detection by leveraging ResNet152V2, which achieves superior accuracy (95%) compared to SVM, CNN-LSTM hybrid, and Random Forest models. By using high-resolution drone imagery and real-time data processing, the system enables early disease identification and targeted pesticide application, reducing chemical usage and minimizing environmental impact. The incorporation of 5G connectivity ensures instant data transmission with low latency, enabling real-time monitoring and decision-making. This allows farmers to respond promptly to crop health issues, preventing large-scale yield losses. The smart spraying mechanism ensures optimal pesticide distribution, reducing waste, lowering costs, and promoting sustainable farming practices.

Furthermore, the system offers improved scalability and adaptability, making it suitable for various types of crops and farming conditions. The use of automated data analytics provides farmers with valuable insights into soil health, moisture levels, and weather patterns, enhancing overall farm management efficiency. Overall, this system offers a scalable, cost-effective, and eco-friendly solution for modern agriculture, boosting farm productivity and profitability while conserving resources. Future improvements could include enhanced deep learning models, larger and more diverse datasets, and the integration of IoT-based soil sensors to further refine disease detection accuracy and optimize resource management.

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