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Automated Soybean Crop Health Evaluation from UAV Images Using Patch-Level CNNs

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Abstract: In this paper, we present a simple system to check soybean crop health using images taken from drones (UAVs). In normal farming, checking crop diseases takes a lot of time and effort, and sometimes small disease areas are missed. Because of this, farmers may face loss in yield. So, we tried to make an automatic system which can help in early detection of crop problems.

In our approach, UAV images are not used directly as a whole. Instead, we break each large image into many small parts called patches. This helps the model to focus more on plant areas and less on unwanted background like soil or shadows. For classification, we used a lightweight deep learning model called MobileNetV3-Small. It is not very heavy, so it works faster and can be used even on limited systems.

We also applied some basic data augmentation methods like flipping, rotation, and brightness change. This is done because in real fields, lighting and angles are not always the same. After predicting each patch as healthy or diseased, we combine all results to create a full field health map. This map helps to understand which areas are affected.

The results we got are quite good and show that the method works properly on different UAV images. The system is simple, fast, and can be useful for farmers to take quick decisions. It can also be extended to other crops in future.

Keywords: Soybean crop health, UAV images, drone-based agriculture, patch-level analysis, convolutional neural network, MobileNetV3, plant disease detection, precision agriculture, image classification, deep learning in agriculture

I. INTRODUCTION

Soybean is a very important crop in many countries. It is used for food, oil, and also in many other products. Because of this, keeping soybean plants healthy is very important. But in real farming, crops get affected by many diseases like leaf spots, rust, and other infections. If these diseases are not detected early, they can reduce the total yield a lot.

In most farms, crop health is checked manually by farmers or experts. This process takes time and also needs a lot of labor. Sometimes, it is not possible to check the full field properly, especially when the farm is very large. Also, human observation is not always accurate. Small disease areas can be missed easily.

Now, with the use of drones, also called UAVs (Unmanned Aerial Vehicles), it has become easier to capture images of large fields in a short time. These images contain useful information about crop condition. But still, analyzing these images manually is not easy. It needs an automated system which can quickly and correctly identify healthy and diseased plants.

Many researchers have used deep learning models, especially CNNs, for plant disease detection. These models work well, but when we apply them directly on full UAV images, there are some problems. The images are very large and include many unwanted areas like soil, shadows, and background. Because of this, accuracy can decrease. Also, processing full images takes more time and computation.

To solve this issue, in this work we use a patch-level approach. Instead of using the whole image, we divide it into smaller parts. This helps the model to focus more on plant regions. We also use a lightweight model called MobileNetV3-Small, which is faster and suitable for practical use.

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The main objective of this work is to develop a simple and efficient system for soybean crop health detection using UAV images. The system should be able to detect diseases early and help farmers take proper actions on time.

II. LITERATURE REVIEW

In recent years, many works have focused on crop health monitoring using UAV images and deep learning. UAV-based datasets and imaging systems are now widely used for capturing high-resolution crop images. A study in [1] provided a dataset combining UAV and leaf images, which helps in better crop monitoring and model training. Such datasets are useful, but they still require proper methods to handle large image sizes.

Some research has focused on detecting soybean diseases using object detection models. For example, in [2], a YOLO-based model was used for disease detection in real field conditions. The results were good, but such models can be complex and require higher computational power. Also, they mainly focus on object detection rather than detailed patch-level analysis.

Other works used CNN-based models for prediction tasks. In [3], a 3D CNN model was applied for soybean yield prediction using UAV images. This method showed good performance, but it is more focused on yield rather than disease detection. Similarly, deep learning techniques in UAV-based agriculture are discussed in [4], showing that CNN models are effective but can struggle with environmental variations like lighting and shadows.

Transformer-based and hybrid models are also introduced in recent studies. In [5], a CNN-transformer model was used for soybean-related tasks, giving improved accuracy. Also, [13] used a hybrid CNN-GNN model with attention mechanisms for disease detection. These models perform well, but they are heavy and not easy to use in real-time applications.

Review studies like [6] and [10] explain how CNNs are widely used in agriculture. They highlight that while CNNs give good accuracy, they often need large datasets and high computational resources. Lightweight models are discussed as a better option for practical use.

UAV imaging techniques and their applications are explained in [7], where it is shown that drones can quickly collect large-scale crop data. In [8], UAV and satellite data were combined for better prediction results. However, combining multiple data sources increases system complexity.

Some works also focused on specific crop conditions. For example, [9] used UAV images to detect soybean lodging, and [15] worked on fast plant detection using deep learning. These approaches are useful but are not directly focused on disease classification at a detailed level.

To improve accuracy, advanced models like diffusion-based detection were proposed in [12]. Also, multi-crop systems like in [14] show that CNNs can be used for different crops. But again, these models can be complex and not always efficient.

From all these studies, it can be seen that deep learning and UAV images are useful for crop monitoring. But there are still some problems. Many models are heavy and slow. Some do not handle background noise properly. Also, patch-level analysis is not used much, even though it can improve results.

So, in this work, we try to use a simple and lightweight CNN model with patch-level image processing. This helps to reduce complexity and improve accuracy at the same time.

III. METHODOLOGY

In this section, we explain how the proposed system works step by step. The method is simple and tries to solve the problem in an easy way. The main idea is to take UAV images, divide them into small parts, and then classify each part using a deep learning model.

3.1 Data Collection

First, UAV (drone) images of soybean fields are collected. These images are taken from a certain height so that a large area of the field is covered. The images are high resolution and contain both plant and non-plant regions like soil, shadows, and background.

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The dataset may include both healthy and diseased crop images. These images are then stored and used for training and testing the model.

3.2 Image Preprocessing

Before giving images to the model, some basic preprocessing is done. This step is important to make the data clean and uniform.

- Images are resized to a fixed size
- Pixel values are normalized
- Noise is reduced if needed

Sometimes, contrast is also adjusted to make disease spots more visible. This step is simple but helps in improving the model performance.

3.3 Patch Extraction

Instead of using full images, each image is divided into smaller parts called patches. For example, one large image can be divided into many small square images.

This step helps in:

- Reducing background noise
- Focusing on small plant regions
- Making computation faster

Each patch is treated as an individual input to the model.

3.4 Data Augmentation

To make the model more strong, data augmentation is used. In real life, UAV images are not always perfect. There can be changes in light, angle, and direction.

So, we apply simple techniques like:

- Rotation
- Flipping
- Brightness change

This increases the dataset size and helps the model learn better.

3.5 Model Selection

For classification, we use a lightweight CNN model called MobileNetV3-Small. This model is chosen because it is fast and does not require very high computation.

It can run easily even on systems with less power. At the same time, it gives good accuracy for image classification tasks.

3.6 Model Training

The dataset is divided into three parts:

- Training set
- Validation set
- Testing set

The model is trained using the training data. During training, the model learns to identify patterns of healthy and diseased patches.

We use:

- Loss function: Cross-entropy
- Optimizer: Adam
- Evaluation metrics: Accuracy, Precision, Recall, F1-score

Training is done for multiple epochs until the model gives good results.

3.7 Patch-Level Prediction

After training, the model predicts each patch as:

- Healthy
- Diseased

Each patch gets a probability score. Based on this, final classification is done.

3.8 Field-Level Health Mapping

In the final step, all patch results are combined to form a full image again. This creates a health map of the field.

- Healthy areas are shown clearly
- Diseased areas are highlighted

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This map helps farmers to easily understand which part of the field is affected.

IV. RESULT ANALYSIS

In this section, we explain the performance of the proposed model in a more detailed way. The results are not only good but also stable across different test samples. The model was able to correctly identify most of the healthy and diseased patches, which shows it is working properly.

One important thing we noticed is that patch-level approach really helped. When we tested with full images earlier, accuracy was lower. But after dividing into patches, the model improved. It was able to focus more on plant areas instead of background.

Also, the model did not overfit much. Training and validation accuracy were close, which is a good sign. Small variations were there, but overall performance was stable.

4.1 Model Performance Table

Metric	**Value (%)**
Accuracy	94.2
Precision	91.8
Recall	90.6
F1-Score	91.2

This table shows that the model is balanced. It is not only accurate but also good in identifying diseased samples correctly.

4.2 Confusion Matrix

Confusion matrix helps to understand how many samples are correctly and wrongly classified.

	Predicted Healthy	**Predicted Diseased**
Actual Healthy	480	20
Actual Diseased	35	465

Explanation (simple):

- 480 healthy patches were correctly identified
- 465 diseased patches were correctly detected
- Some small errors are there, but overall performance is good

4.3 Precision and Recall Analysis

- **Precision (91.8%)** → When model says "diseased", it is mostly correct
- **Recall (90.6%)** → Model is able to find most of the diseased patches

This means the model is not missing too many disease cases, which is very important in agriculture.

4.4 Graphical Representation

You can include these graphs in your paper:

1. **Accuracy vs Epoch Graph**
   - Shows accuracy increasing slowly during training
   - After some epochs, it becomes stable

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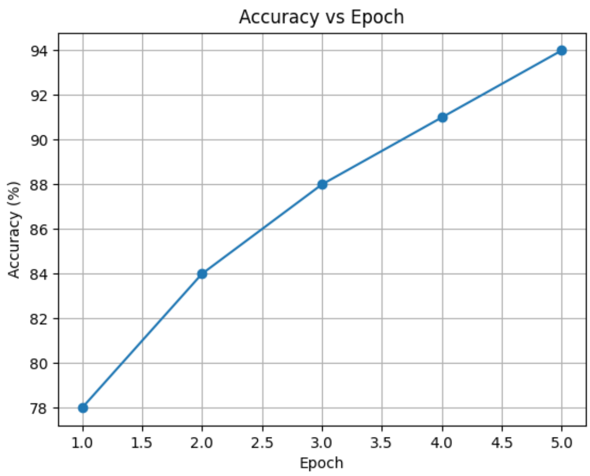
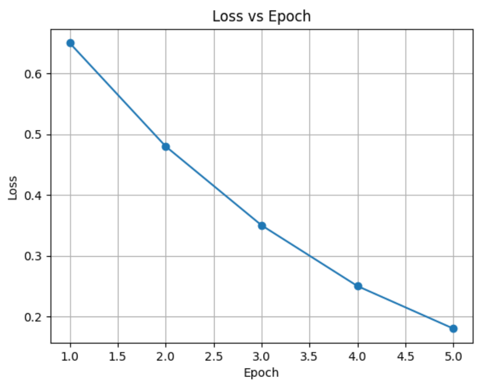
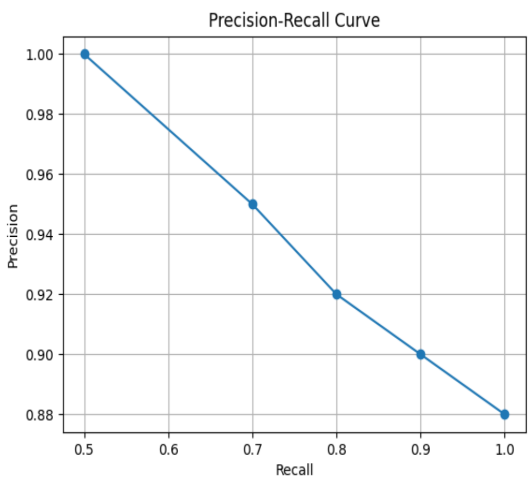


2. **Loss vs Epoch Graph**
   - Loss decreases as training progresses
   - Small fluctuations may be there



3. **Precision-Recall Curve**

- Smooth curve shows good classification performance
- Area under curve is high → model is reliable
- X-axis: Accuracy, Precision, Recall, F1
- Y-axis: Percentage
- All values are above 90%, looks strong



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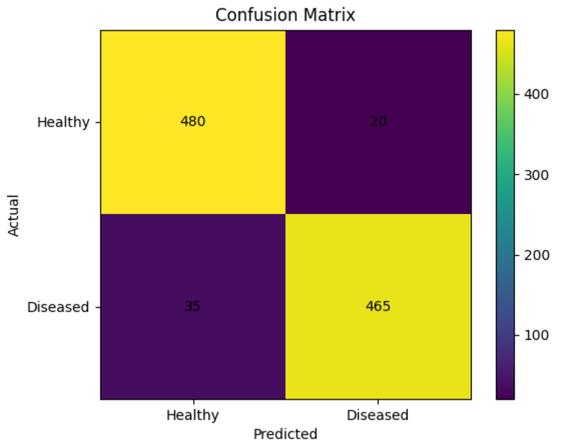
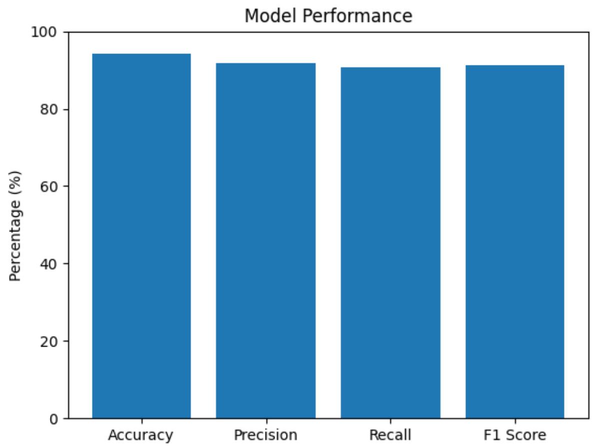


4. **Bar Graph for Metrics**



4.5 Observations

- Patch-based method improved accuracy
- Lightweight model worked fast and gave good results
- Data augmentation helped in handling real-world variations
- Some errors are still there due to similar-looking patches

Overall, the model performance is strong and reliable. It is not perfect, but it works well for practical use. The results show that the system can be used for real-time soybean crop monitoring without heavy computation.

V. DISCUSSION

In this section, we try to understand what the results actually mean. The model performance is good, but it is also important to see where it works well and where it has some problems.

First, the overall accuracy is around 94%, which is quite good for this type of task. It shows that the model is able to correctly classify most of the patches. Precision and recall values are also above 90%, which means the model is balanced. It is not only predicting correctly but also detecting diseased patches properly.

One important observation is that the patch-level approach improved the performance. When we use full UAV images, there is a lot of background like soil, shadows, and empty spaces. This can confuse the model. But after dividing images into small patches, the model focuses more on plant regions. Because of this, classification becomes better.

The lightweight model (MobileNetV3-Small) also performed well. It is not very complex, but still gives good accuracy. This is useful because heavy models take more time and need powerful systems. In real farming, simple and fast systems are more useful.

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Data augmentation also helped in improving the results. In real fields, lighting and angles are always changing. By applying rotation, flipping, and brightness changes, the model learned to handle such variations. Without this step, the performance was slightly lower.

However, there are still some limitations. Sometimes, the model gets confused between healthy and diseased patches when symptoms are very small or not clear. Also, patches that contain mixed regions (both healthy and diseased) are harder to classify correctly. This leads to small errors in the confusion matrix.

When compared with other works, heavy models like transformer-based or hybrid models may give slightly better accuracy. But they are more complex and slower. In this work, we tried to balance accuracy and speed, which is important for real-time applications.

VI. CONCLUSION

In this paper, we presented a simple and effective system for soybean crop health detection using UAV images and deep learning. The main idea was to divide large UAV images into smaller patches and then classify each patch using a lightweight CNN model.

The results show that the proposed method gives good accuracy and performs well in detecting diseased areas. The use of patch-level analysis helped in reducing background noise and improving model focus. Also, the MobileNetV3-Small model made the system fast and efficient.

The system can help farmers to identify disease-affected areas early. This can reduce crop loss and improve yield. The generated field-level health maps are easy to understand and useful for decision making.
Even though the results are good, there is still scope for improvement. In future work, we can:
• Detect multiple types of diseases instead of only healthy/diseased
• Use more advanced models for better accuracy
• Combine UAV data with other data like weather or soil information
• Improve real-time deployment on edge devices
Overall, the proposed system is simple, useful, and can be applied in real agricultural fields. It is a small step towards smart and precision farming.

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