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# Assessment of Goss Wilt Disease Severity Using Machine Learning Techniques Coupled with UAV Imagery

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***Abstract.***

*Goss Wilt has become a common disease in corn fields in North Dakota. The current method to identify the disease is through visual inspection of the field, which is inefficient, and can be subjective, yielding misleading results due to evaluator's perception and fatigue. Therefore, developing an automated tool that can reliably and accurately detect and assess Goss's Wilt's severity would be a welcome development for researchers and farmers. With that goal in mind, this study implemented machine learning (ML) algorithms to assess the severity of Goss's Wilt disease from an unmanned aerial vehicle (UAV) image collected over a corn field located in Horace, ND, USA. After the initial image stitching process, a total of 270 plot images were obtained. Augmentation techniques were used to create a new dataset containing 1326 images. From each plot image, two different types of features were extracted: textural (contrast, dissimilarity, homogeneity, angular second moment) and color (hue, saturation, value, brightness, chromatic components: a* and b*, red, green, blue). A total of nine different ML algorithms, including Logistic Regression, Ada Boost, Gradient Boosting, Support Vector Machine (linear), Support Vector Machine (polynomial), Multilayer Perceptron, Random Forest, Naive Bayes, and*

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*K-Nearest Neighbors, were implemented for assessing disease severity. The augmented dataset was divided into training (80%) and testing (20%) subsets. Models were evaluated using metrics such as precision, recall, and F-score. Results showed that random forest achieved higher precision (0.83), recall (0.83), and F-score (0.83) and outperformed other classifiers in this study. Therefore, the use of UAVs to collect images, coupled with Random Forest algorithm for image analysis, can be a potential tool for Goss's Wilt disease severity assessment in corn.*

***Keywords.***
*corn, Goss's Wilt, UAV imagery, Machine Learning.*

# 1. Introduction

Plant disease has been identified one of the biggest threats to food security and production. The global population will be nearly 10 billion by 2050 (FAO, 2017). Farmers worldwide will need to increase crop production, either by adding new acreage or raising productivity on existing farms via fertilizer, irrigation, and modern agricultural technology such as precision agriculture (Elferink and Schierhorn, 2016). Around 10% of global food production is lost due to plant diseases (Strange et al., 2005; Savary et al., 2006). Plant disease can cause significant yield losses, ranging from 10% to 41%, for major crops such as wheat, rice, maize, potato, and soybean (Savary et al., 2019). This indicates that enhancing disease control can play a significant role on meeting the increasing demand for food by 2050 as the worldwide population continues to grow.

Corn (Zea mays L.) accounts for more than 95% of the feed grain produced in the United States (USDA ERS, 2019). Between 2012 and 2015, the estimated overall yield loss due to corn Goss's Wilt in the United States and Canada was over 500 million bushels (Mueller et al., 2016). In addition, it is a major corn yield-limiting disease in North Dakota, USA causing up to 41% yield losses on a susceptible corn hybrid (Friskop, 2021). This disease is very reliant on environmental circumstances and spreads swiftly when temperatures range between 65oF to 85oF at moist conditions (Hu et al., 2020). However, disease identification in its early stage is challenging due to the visual similarity of other foliar diseases (Stewart's wilt) (Hu et al., 2020) and it may require individuals trained in plant pathologist to accurately identified the disease.

Goss's Wilt can be controlled through the use of non-host crops such as soybeans, dry beans, small grains, or alfalfa in a continuous rotation with corn in order to reduce the number of pathogens in the soil (Merrel, 1997), but the most effective method of controlling it is through the use of resistant hybrids (Treat and Tracy, 1990). As a result, more research into disease assessment has been prioritized to prevent yield losses by identifying resistant hybrids during the breeding process. That makes even more urgent the need to develop a solution that can improve the efficiency to screen hundreds or thousands of small field plots on a short period of time. Relying on trained individuals to carry out such tasks can be expensive, labor intensive, and result inaccurate data due to evaluator's fatigue. This illustrates a real need for researchers to develop solutions that are quick, reliable, and automated in nature.

Unmanned aerial vehicles (UAVs) have gained appeal in recent years as an alternative to handheld techniques due to their ability to collect imagery more quickly and efficiently. Several researchers used UAV with machine learning (ML) algorithms and achieved significant performance in plant disease classification (Zhou et al., 2020), detection (Duarte et al., 2020), and identifications (Wang et al., 2020). However, very few studies have been conducted using UAV imagery incorporated with ML algorithms to identify corn diseases. Das et al. (2021) assessed corn Goss wilt using UAV imagery and seven different ML algorithms and obtained satisfactory classification results for low- and high-severity disease infestation.

Currently, ML techniques have gain popularity due to fast reliable and accurate plant disease assessment (Flores et al., 2021; Zhang et al., 2020). Several researchers have implemented ML algorithms for corn disease assessment including southern corn rust detection and classification (Meng et al., 2020), corn gray leaf spot, corn rust, corn big spot (Kusumo et al., 2018; Liu et al., 2020), leaf large spot, small spot, and brown spot disease (Ren et al., 2019). Kusumo et al., (2018) implemented different ML models to detect corn diseases including Gray Leaf Spot, Common Rust, Northern Leaf Blight from healthy leaves achieved satisfactory results (around 90% of accuracy). They extracted color features such as red, green, blue and local features. They observed color-based feature had higher contribution to have better classification accuracy. Aurangzeb et al., (2020) achieved 98.7% leaf disease accuracy recognition by using advance ML techniques and fusing the extracted features for corn and potato. Ren et al. (2019) conducted an experiment to classify leaf large spot, small spot, and brown spot disease from healthy leaf using a ML algorithm. They extracted textural (Hu invariant moment, contrast, energy, and homogeneity), color and shape features from the images and achieved 89.38% classification accuracy. Some of the common ML algorithms being used in recent years for corn disease assessment are random forest (RF), decision tree (DT), naive bayes (NB), support vector machine (SVM), K-nearest neighbors (Panigrahi et al., 2020; Kusumo et al., 2018; Liu et al., 2020; Meng et al., 2020)

Therefore, the development of UAV based system incorporated with ML algorithms can be valuable addition to assess Goss's Wilt toward developing faster, reliable, and cost-effective disease assessment system. Thus, the objective was to evaluate the performance of several ML classifiers on identifying Goss's Wilt severity on corn under field conditions based on UAV collected images.

# 2. Material and Methods

## 2.1 Data Collection and Preparation

The severity of corn Goss's Wilt was assessed on July 19, 2021 by a trained plant pathologist in a field experiment (52 field plots) located in Horace, ND. Plots were rated visually based on the vertical canopy lesion movement (1–9) and the severity of the leaf tissue lesion (1–9). The average percent disease severity (PDS) for a plot as calculated using the height and severity data.

A DJI Matrice 600 Pro (DJI-Innovations, Inc., ShenZhen, China), outfitted with a 42-megapixel RGB Sony Alpha 7R III camera (Sony Corporation, Tokyo, Japan) and a GeoSnap system (Field of View LLC, Fargo, USA) to trigger the camera and to collect geotagging information for each image. The UAV was flown at 150 ft AGL (above ground level), at a speed of 2.5 meters per second, and images (7952 x 5304 pixels) were collected with 80% side and front overlap. The images were taken on July 20, 2021, at 3:00 PM, under sunny weather conditions.

The collected images were transferred into a desktop computer (Intel® Core™ i9-10900K @ 3.70 GHz), where they were processed with PIX4Dmapper by PIX4D (Pix4D SA, Lausanne, Switzerland) to generate a georeferenced orthomosaic image. QGIS (QGIS Development Team, 2021) was used to create a shapefile containing the 52 plots (ground truth plots) on top the orthomosaic image. The plot shapefile was later fed into a program developed by Gris (2021) in Python (v3.8) to extract the plot images from the original unstitched RGB images. The program is based on source code developed by Tresch et al., (2019) which is publicly available on GitHub (https://github.com/UTokyo-FieldPhenomics-Lab/EasyMPE). Since the same plots were captured in more the one image, due to the 80% overlap flight parameter, the program returned a total of 270 plot images. Plots were divided into two classes based on the PDS value: medium severity (142 plots) and high severity (128 plots). Figure 1 shows the flow diagram of the entire process. A total of 1326 images was prepared from the plot images using augmentation techniques including flipping (horizontal and vertical) images and translating images by shifting pixels with different values in x and y directions. Data augmentation was done by using a python program developed by Dawson (2019) which is publicly available on GitHub (https://github.com/codebox/image_augmentor). From that dataset, 617 images were in the medium severity class, while 710 images were in the high severity.

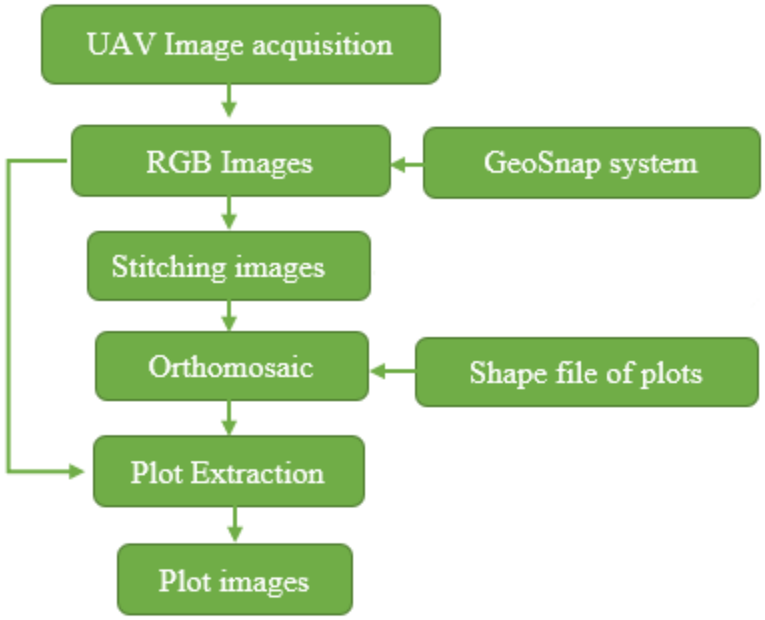


**Figure 1. Flow diagram showing processing steps followed to extract images for individual plots from the raw images using the orthomosaic to locate those plots.**

## 2.2 Training and validation of machine learning classifiers

A total of 14 different color and textural based features were extracted from the augmented dataset using a custom program developed using Scikit-learn (Pedregosa et al., 2011) in Python. Color based features included hue, saturation, value, brightness, and chromatic components: a* and b*, red, green, and blue. Textural based features included contrast dissimilarity, homogeneity, and Angular Second Moment (ASM). Textural features were extracted using Gray-Level Co-occurrence Matrices (GLCMs) (Haralick et al. 1973). The GLCM's textural properties were determined using eqs. (1), (2), (3), (4), and (5) correspondingly.

$$Contrast = \sum_{i,j=0}^{levels-1} P_{ij}(i-j)^2 \quad \text{(eq. 1)}$$

$$Dissimilarity = \sum_{i,j=0}^{levels-1} P_{ij} \mid i-j \mid \quad \text{(eq. 2)}$$

$$Homogeneity = \sum_{i,j=0}^{levels-1} \frac{P_{i,j}}{1+(i-j)^2} \quad \text{(eq. 3)}$$

$$Angular\ Second\ Moment\ (ASM) = \sum_{i,j=0}^{levels-1} P_{i,j}^2 \quad \text{(eq. 4)}$$

$$Energy = \sqrt{ASM} \quad \text{(eq. 5)}$$

where $P_{ij}$ is the probability in a cell, where *i* and *j* are the row and column numbers of the image window, respectively.

A total of nine of ML algorithms including Logistic Regression (LR), Ada Boost (AB), Gradient Boosting (GB), Support Vector Machine Linear (SVM: linear), Multilayer Perceptron (MLP), Random Forest (RF), Naive Bayes (NB), K-Nearest Neighbors (KNN), and Support Vector Machine Polynomial (SVM: polynomial), were implemented to classify plot images using Scikit-learn (Pedregosa et al., 2011) package in Python. Models were evaluated using metrics such as precision (eq. 6), recall (eq. 7), and F-score (eq. 8).

$$Precision = \frac{TP}{TP + FP} \quad \text{(eq. 6)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{(eq. 7)}$$

$$F - score = \frac{2 * Recall * Precision}{Recall + Precision} \quad \text{(eq. 8)}$$

where TP= true positive, TN= true negative, FP= false positive, FN= false negative.

## 3. Results and Discussion

Random Forest (RF) achieved comparatively better precision (0.83), recall (0.83), and F-score (0.83) than the other tested algorithms in this study (Table 1). The confusion matrix for corn Goss's Wilt classification is shown in Figure 3, where "0" and "1" represent medium and high severity classes, respectively (Figure 2). The MLP yielded the highest number of TP (121), FP (102) and the lowest number of FN (17) (Figure 2). The highest number of FP resulted in a poor precision value (0.54) and the lowest number of FN resulted in a good recall value (0.88), which together contributed to achieving a poor F-score (0.67) for MLP (Table 1). Similarly, the lower precision and higher recall values caused greater imbalances and resulted in poor F-scores for the LR (0.67), SVC-linear (0.67), SVC-polynomial (0.66), and Gaussian NB (0.62) classifiers. On the other hand, KNN, AB, and GB classifiers achieved lower FP and FN values (Figure 2), which yielded quite good precision and recall values and resulted in better F-scores (Table 1). Overall, RF performed well among other classifiers as it yielded a satisfactory F-score (0.83). The probable reason for achieving better classification results, among others, is that RF uses random instances of the training dataset and subsets of features (bootstrapped sample) for training decision trees (voting classifiers). The class that receives the most votes from the decision tree is considered the final prediction class, which is referred to as the aggregation. The results of this aggregation gradually reduce bias and variance, which might be the reason for the better classification result in this experiment.

**Table 1. Evaluation of machine learning models on detecting Goss's Wilt in corn based on high resolution RGB images collected with a UAV.**

| Machine Learning Classifiers | Precision | Recall | F-score |
|---|---|---|---|
| Logistic Regression | 0.62 | 0.73 | 0.67 |
| Ada Boost | 0.69 | 0.66 | 0.68 |
| Gradient Boosting | 0.77 | 0.72 | 0.74 |
| Support Vector Machine (linear) | 0.61 | 0.75 | 0.67 |
| Multilayer Perceptron | 0.54 | 0.88 | 0.67 |
| Random Forest | 0.83 | 0.83 | 0.83 |
| Gaussian Naive Bayes | 0.55 | 0.70 | 0.62 |
| K-Nearest Neighbors | 0.75 | 0.77 | 0.76 |
| Support Vector Machine (polynomial) | 0.58 | 0.77 | 0.66 |

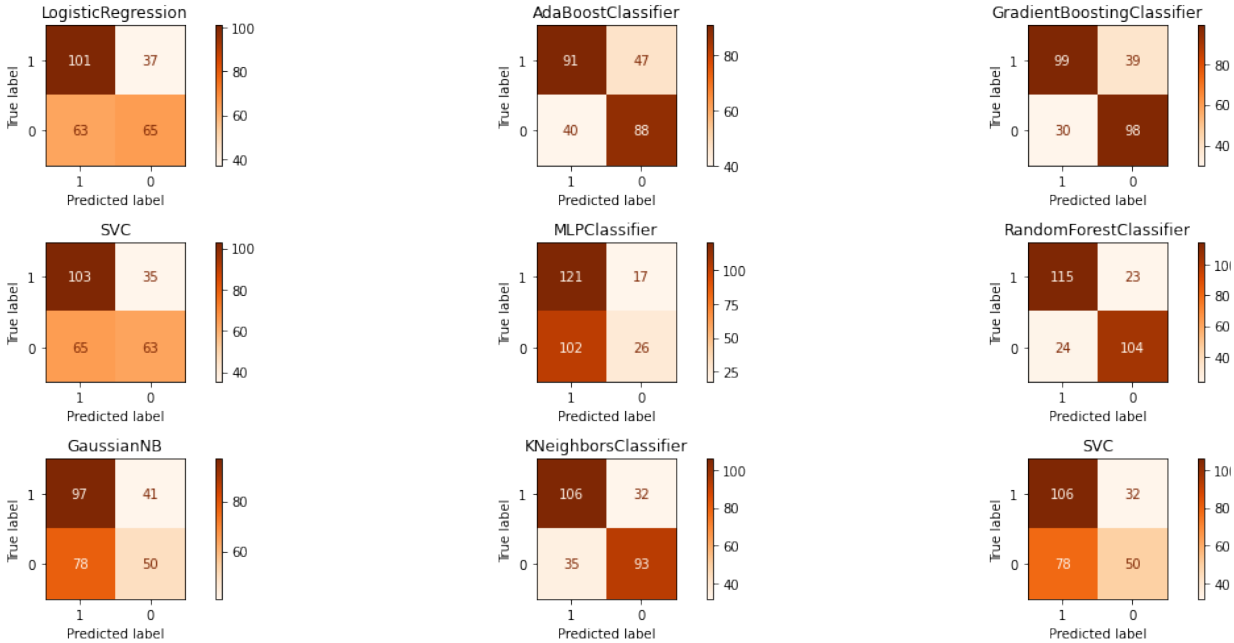


**Figure 2. The confusion matrix on the assessment of Goss's Wilt in corn using high-resolution RGB images captured by a UAV.**

However, the results of RF could be improved by optimizing and experimenting with hyperparameters, which can be done in the future. This study experimented on a small Goss's wilt trial field and achieved an 83% of F-score on classifying medium and severe plots. This indicates a potential for assessing Goss wilt for commercial fields. This study did not investigate micronutrient properties of soil, drought status, and dead plants while assessing Goss Wilt, which can be done in the future using UAV imagery incorporated with ML and deep leaning techniques.

## 4. Conclusion

Random Forest classifiers outperformed other classifiers in this study, with a F-score of 0.83, in categorizing Goss's Wilt disease in corn plots based on UAV images. Results indicate the potential to use UAV images coupled with RF classifier for the development of an automated corn Goss's Wilt disease field assessment solution. The next steps on this research will be to increase RF classification accuracy by optimizing parameters of its classifiers. Moreover, advance techniques such as deep learning algorithms will be investigated and assessed on the performance to detect and classify Goss's Wilt disease in corn under field conditions.

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