BANANA REIGNS WILT BASED ON MACHINE LEARNING AND UAV-BASED MULTISPECTRAL IMAGERY

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ABSTRACT
Reigns Wilt disease is one of the diseases that cause serious damage to crops in tropical monsoon regions. Among them, banana wilt disease is one of the common and worrying problems, especially in Vietnam. Therefore, monitoring and surveillance of reigning wilt disease in crops in general and bananas in particular is an important task, helping to improve crop productivity and quality. The objective of this study is to develop a method based on machine learning and data from unmanned aerial vehicles (UAVs), namely AdaBoost (ADB), Deep neural network (DNN), Random Forest (RF), and Support vector machine (SVM) models, to monitor banana reigns wilt. The study was carried out in Ly Nhan district, Ha Nam province, Vietnam. To evaluate the performance of the proposed models, statistical indices such as the area under the curve (AUC), the root mean squared error (RMSE), and the mean absolute error (MAE) were used. The results showed that all proposed models, combined with UAV data, were successful in zoning and monitoring banana wilt disease. The ADB model gave the best results with an AUC value of 0.98, followed by the DNN model with an AUC of 0.96, RF with 0.95 and SVM with 0.94. In addition, the results also showed that areas with high and very high levels of leaf wilt disease were concentrated in the south and the edge of the garden, possibly due to the influence of external factors and ineffective care conditions. This study is important to provide an effective and accurate tool to monitor plant health, especially banana plants. The research results not only help to detect diseased areas early, but also help farmers and managers take timely interventions, thereby improving crop productivity and quality while contributing to the development of sustainable agriculture.

Key-words: *Banana Reigns Wilt; machine learning; UAV; Ha Nam; Vietnam*

1. INTRODUCTION

Banana is one of the important cash crops, widely cultivated in tropical humid countries, and a resource for many countries such as China, Vietnam, India, Brazil, and Africa (Shen, Xue et al. 2019, Selvaraj, Vergara et al. 2020). In addition to its economic role, banana plays an significant role in food security and sustainable rural development.

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According to FAO statistics, the banana cultivation area in the world is approximately 850.000 ha; among them, Vietnam has one of the highest banana cultivation countries in the world with about 155.000 ha, representing approximately 19% of the fruit cultivation area in the country (Zhang, Li et al. 2022). Among bananas, Royal Dai Hoang bananas play an important role in international markets such as Japan and Korea. In Vietnam, Royal Dai Hoang bananas are not only the main source of income for some regions such as Ly Nhan (Ha Nam), but also a symbol of culture and politeness. However, the frequent occurrence of some diseases, such as yellow leaf disease and leaf wilt, has seriously affected the income sources and food security issues of some countries, including Vietnam (Nguyen, Dang et al. 2024). This disease can occur throughout the plant growth process and spread rapidly (Ploetz 2015). Therefore, the detection of areas or plants infected with yellowing disease plays an important role in the rapid treatment of the disease and its control.

From the literature review, there are several methods for monitoring and distinguishing diseases of crops in general and bananas in particular. Traditionally, field monitoring is considered an effective method with high accuracy to detect banana diseases (Nalawade, Nagap et al. 2020). However, this method is very costly and time consuming. In recent years, with the development of remote sensing sensors, remote sensing has been considered one of the feasible technologies for detecting and evaluating diseases. Several diseases have been detected by remote sensing, such as Fusarium head blight, grey leaf spot in maize, and late blight disease and bacterial spot in tomato (Ye, Huang et al. 2020, Mohidem, Che'Ya et al. 2021, Zhang, Li et al. 2022). When plants are infected with diseases, the colour and biochemical characteristics also change. All this has been reflected in the spectral characteristics of plants. Several studies have used vegetation indices to identify diseases in leaves and canopy. Zhang, Li et al. (2022) used high-visible-band images, five-multispectral-band images, and vegetation indices (VIs) combined with machine learning models, namely Support Vector Machine (SVM), Random Forest (RF), Back Propagation Neural Networks (BPNN) and Logistic Regression (LR) to detect Banana Fusarium wilt in bananas. Ye et al. (2020) applied eight vegetation indices (VIs) using unmanned aerial vehicle (UAV) combined with binary logistic regression (BLR) statistical model to identify Banana Fusarium Wilt. Ye et al. (2020) applied the normalised difference vegetation index (NDVI), normalized difference red edge index (NDRE), structural independent pigment index (SIPI), red-edge structural independent pigment index (SIPIRE), green chlorophyll index (CIgreen), red-edge chlorophyll index (CIRE), anthocyanin reflectance index (ARI), carotenoid index (CARI) and binary logistic regression to determine the biophysical characteristics of banana plant. However, the spectral bands and vegetation indices present different sensitivities with different diseases, therefore, it is necessary to detect the more appropriate spectral bands and vegetation indices to identify the given diseases.

Satellite images are considered one of the necessary data sources for large-scale agricultural monitoring. Previous studies have used high-resolution satellite images to detect plant diseases (Deng, Zhu et al. 2020). Oumar and Mutanga (2013) used Worldview 2 images to monitor aphid diseases in plantation forests. Meanwhile, Shi and colleagues used Planet Scope images to detect rice leaf scab. However, the characteristics of canopy structure and biological impacts on plants often differ at small scales, but in fact their spectral reflectance is similar in medium-resolution satellite images such as Sentinel and Landsat. In addition, high-resolution satellite images are often limited by their cost. In recent years, several multispectral sensors, including red-edge bands, have been designed for unmanned aerial vehicle (UAV) platforms to detect agricultural diseases. With the development of UAV technology, researchers acquire images to extract crop information faster due to their advantage in high spatial resolution (Ye, Cui et al. 2020, Ye, Huang et al. 2021). However, along with the rapid development of remote sensing data, research and development of new methods are needed to process these data accurately and efficiently.

In recent years, with advances in computer science, several studies have used machine learning for satellite image classification. Machine learning establishes relationships between the spectral features of images and samples to identify unclassified images. Algorithms include decision tree (Ye, Huang et al. 2020), support vector machine (Senthilraj and Parameswari 2022), random forest (Ye, Cui et al. 2020), artificial neural network (Ye, Cui et al. 2020) and k-nearest neighbours (Rathnayake, Samuel et al. 2023). Although significant advances have been made in research on mulch classification in general and agricultural disease detection in particular, these algorithms still have limitations, especially with regard to the accuracy of the classification results. These limitations are particularly evident when the data samples used in the learning process are unevenly distributed. Furthermore, each algorithm is tailored to a specific dataset, making it necessary to explore and adjust algorithms for each type of data.

Among these algorithms, SVM, RF, ADB, and DNN are the most popular algorithms for classifying satellite images. Each algorithm excels in specific cases, for example, SVM is very effective for small data with well-defined boundaries between . Additionally, SVM optimises the search for a "hyperplane" to divide data classes so that the distance between points of different classes is the largest, helping to improve the classification accuracy. Furthermore, SVM has the advantage of analysing unevenly distributed data, through the selection of appropriate kernels. This helps the SVM model achieve high accuracy even when the data is imbalanced. This is especially important when using the SVM model to solve classification problems in developing countries, where data collection is a major challenge related to finance and data sharing policies (Hearst, Dumais et al. 1998, Karamizadeh, Abdullah et al. 2014).While RF handles very well and noisy data. Additionally, RF is considered to have advantages in dealing with data loss and unbalanced data in the training set. Furthermore, RF is capable of mitigating the overfitting problem, helping the model achieve high accuracy even when dealing with large and complex data sets. Finally, one of the advantages of RF is that it does not require data normalisation, which helps to minimize data preprocessing. Moreover, AdaBoost is considered as an efficient algorithm for unbalanced data sets, This is important when monitoring plant health, where the number of diseased plants is lower than the number of healthy plants (Ao, Li et al. 2019, Zhu 2020). In addition, ADB has the advantage of minimising the impact of noise in the data, allowing the model to be highly accurate even when the data are noisy. In final, DNN was necessary to handle large amounts of data. In addition, DNNs have the ability to automatically adjust and optimise, allowing the model to recognize complex problems (Li 2018, Ahmed, Alam et al. 2023). The use of these algorithms can explore the different activities and select the appropriate method to identify crop diseases. Thus, the objective of this study is to identify banana diseases, such as banana Reigns Wilt disease, based on machine learning and data collected by UAV (drones) in Ly Nhan district, Ha Nam province. The results of this study support the identification of areas affected by Banana Reigns Wilt disease, helping farmers develop disease treatment strategies and adjust their cultivation practices.

2. MATERIALS AND METHODS

2.1. Study Area

Ly Nhan is a delta district located in the Red River region, in the East of Ha Nam province, with an area of 16,884.31 hectares and a population of about 180,292 people (**Fig. 1**). The topography of the study area is a low-lying plain along the Red River, with an average elevation ranging from 0.7 to 4.5 m. The study area is located in the tropical monsoon climate zone typical of the Northern Delta, with cold and dry winters, hot and humid summers, and heavy rains. The average annual rainfall ranges from 1,700 to 2,200 mm, unevenly distributed by season. The rainy season lasts from May to October, accounting for approximately 75% of the total annual rainfall, with the largest rainfall falling in July, August and September (average 310 - 320 mm/month), which is also the time when storms and floods often occur. The dry season from November to April of the following year accounts for only about 25% of the total annual rainfall, mainly drizzle and light rain.

The Ly Nhan district is blessed with fertile and nutrient-rich alluvial soil and a favourable river system, creating ideal conditions for agricultural development, especially the Royal Dai Hoang banana. Currently, the Royal banana is mainly grown in the communes of Nhan Hau, Nhan Thinh, and Nhan Nghia, with the cultivated area expanding. Royal Dai Hoang is considered one of the main sources of income for people in communes in Ly Nhan district, Ha Nam province. In addition to its economic value, Royal Dai Hoang also makes an important contribution to the culture of the people of Ha Nam province. Royal Dai Hoang is closely associated with many traditions and traditional festivals in the community. For example, Royal Dai Hoang is indispensable on the holidays of the people of Ha Nam. However, the production of Royal Dai Hoang banana still faces many challenges, such as the small and scattered cultivation area, which makes it difficult to apply modern techniques and organise large-scale production. Furthermore, in recent years, Royal bananas have faced pests and diseases, especially leaf wilt disease. Therefore, monitoring and timely detection of infected plants is extremely important, helping farmers develop effective treatment solutions and ensure crop yields.

This study selected 3 Royal Dai Hoang banana gardens for analysis. Garden 1 with an area of 2.4 ha, Garden 2 with an area of 11.4 ha, and Garden 3 with an area of 2.4 ha.

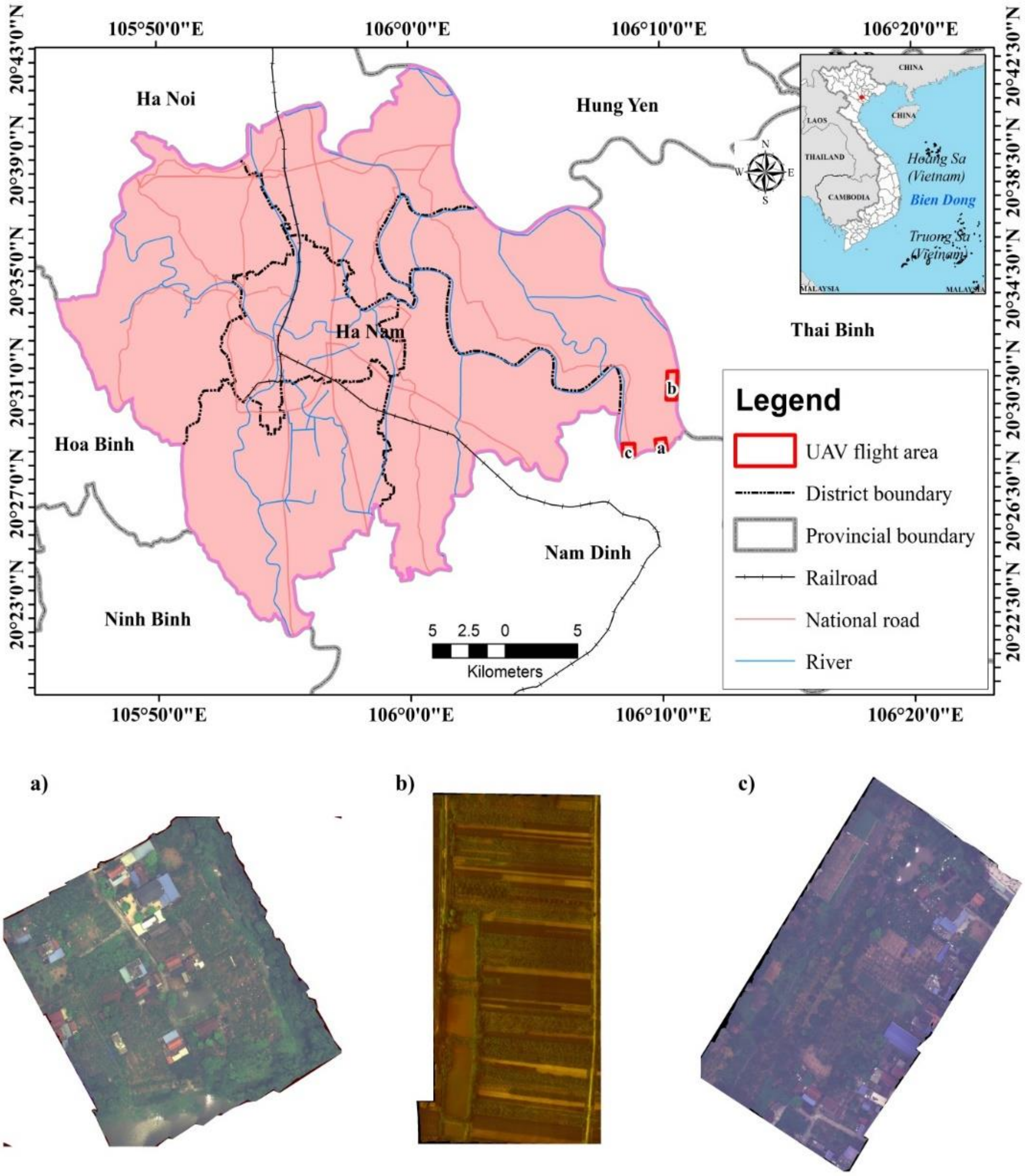

Fig. 1. Location of the study area.

2.2. Field Investigation

In this study, 230 sample plots were collected from eight field missions in 2023 and 2024 to assess the occurrence of reigns wilt banana disease. The size of each sample plot corresponded to a single banana plant. The samples were divided into two categories: healthy samples (230 samples) and diseased samples (230 samples). These samples represent the occurrence or nonoccurrence of banana disease, reflected by external characteristics. The information on each sample was recorded using a GPS.

In addition, this study uses a binary classification. Therefore, the number of diseased samples was equal to that of the non-diseased samples to ensure the balance of the model. Finally, a banana plant was defined as diseased when the rate of yellow leaves relative to the total leaf area exceeded 1% (**Fig. 2**).

Ultimately, 70% of the data set was used to train the machine learning models, while 30% of the data was used to validate the building models. In this study, several rates such as 80/20, 60/40 and 50/50 were used for constructing the machine learning model. However, the rate 70/30 present the results with more precision. In addition, this rate is used in widely previous research (Nguyen, Van et al. 2023).

Fig 2. The reigns wilt banana in study area.

2.3. Data collection using UAVs

In this study, field missions were conducted using DJI Phantom 4 multispectral UAVs. This UAV was equipped with a 6-axis multispectral camera, which is capable of detecting and tracking RTK images. This camera has 5 wavelengths: Blue (R_b): 450 nm ± 16 nm, Green (R_g): 560 nm ± 16 nm, Red (R_r): 650 nm ± 16 nm, Red edge (R_{re}): 730 nm ± 16 nm, Near-infrared (R_{nir}): 840 nm ± 26 nm. The flights on the first study site were carried out from 10:00 to 13:00 on 17 May 2024, covering an area of 24 hectares. The flight at the second study site was carried out from 14:00 to 16:00, covering an area of 18 hectares, and that on the third study site from 17:00 to 18:00, covering an area of 15 hectares on the same day.

2.3.1. Data Preprocessing

Once collected by the UAV, the images were processed in two main steps:

In the first step, the collected images were assembled using tie points in specialised software. At the same time, ground control points (GCPs) were also determined to ensure coordinate and spatial accuracy. This process ensures that the images are properly aligned, providing the foundation for UAV image analysis.

Once the image assembly was completed, a deep processing phase was performed. From the determined control points, the software constructed a triangular mesh (Mesh) and a 3D point cloud (3D point cloud). From there, a digital elevation model (DSM) and an orthomosaic image were created, providing an accurate geospatial basis. Finally, reflectance spectrum maps for colour channels such as blue, green, red, red edge, near-infrared, and NDVI vegetation index were created.

It should be noted that UAV data processing can be performed preliminarily in the field during the flight, allowing timely adjustments to ensure good quality images with a high level of overlap, usually reaching over 75%.

2.3.2. Vegetation Index Building

In this study, five monochromatic spectral bands of UAV images were included; UAVs (Blue (R_b): 450 nm ± 16 nm, Green (R_g): 560 nm ± 16 nm, Red (R_r): 650 nm ± 16 nm, Red edge (R_{re}): 730 nm ± 16 nm, Near-infrared (R_{nir}): 840 nm ± 26 nm) were used to compute vegetation indices and to build a machine learning model (Eq. (1)). Eight vegetation indices were selected in this study: NDVI, RDVI, NPCI, GRVI, GNDVI, GDVI, BNDVI. These indices were selected on available data characteristics,, vegetation characteristics and previous studies. NDVI is one of the important indices in studies on ecology, vegetation growth, and land cover change. In addition, these indices are also widely used in studies of agricultural plant diseases and crop yields (Rouse, Haas et al. 1974). NDVI is computed on spectral reflectance in the red and NIR ranges, which are highly correlated with photosynthetic activities and plant vitality.

$$\mathrm{NDVI} = \frac{\mathrm{R_{nir}} - \mathrm{R_r}}{\mathrm{R_{nir}} + \mathrm{R_r}} \tag{1}$$

GNDVI was chosen to build a crop health monitoring model because it determines the level of chlorophyll variation in leaves (Tucker 1979). Similar to GNDVI, however, instead of using the ratio, GDVI uses the difference between green and near-infrared reflectance to detect changes in chlorophyll in the canopy at small scales (Zhang, Li et al. 2022). GNDVI and GDVI are computed using the following formulas Eq. (2) and Eq. (3):

$$GNDVI = \frac{R_{nir} - R_g}{R_{nir} + R_g} \tag{2}$$

$$GDVI = NIR - Green \tag{3}$$

RDVI is computed on the spectral reflectance in the near-infrared (NIR) and red (RED) regions, which helps assess plant density and canopy cover (Wikantika, Ghazali et al. 2023). High RDVI values indicate healthy plants and dense foliage. RDVI is computed using the following formula Eq. (7):

$$RDVI = \frac{NIR - RED}{\sqrt{NIR + RED}} \tag{4}$$

NPCI was chosen in this study because it assesses plant health by reflecting changes in plant chlorophyll pigments due to infection by disease. High NPCI values indicate diseased plants, which show a lower chlorophyll content (Gao, Ji et al. 2023). The NPCI was calculated using the formula in Eq. (7):

$$NPCI = \frac{RED - Green}{RED + Green} \tag{5}$$

GRVI is computed on the reflectance of the red and green regions, which is used to compute the photosynthetic index and biomass of plants. This index has been widely used in previous studies to monitor the development and growth of plants. High GRVI values indicate healthy plants and strong photosynthesis (Motohka, Nasahara et al. 2010). GRVI is computed according to the formula in Eq. (7):

$$GRVI = \frac{Green - Red}{Green + Red} \tag{6}$$

BNDVI is computed based on the ratio of green and near-infrared reflectance to assess plant health based on chlorophyll changes in plants (Gordillo-Salinas, Flores-Magdaleno et al. 2021). BNDVI is computed on the formula in Eq. (7):

$$BNDVI = \frac{Nir - Blue}{Nir + Blue} \tag{7}$$

2.4. Methodology

The methodology used to monitor Banana Reigns Wilt was structured into five main steps: i) collection of sample plots and UAV data to construct the conditioning factors; ii) data processing; iii) construction of ADB, DNN, RF, and SVM models; iv) evaluation of the accuracy of the proposed models; and v) analysis of the Banana Reigns Wilt map. The methodology is illustrated in **Fig. 3**:

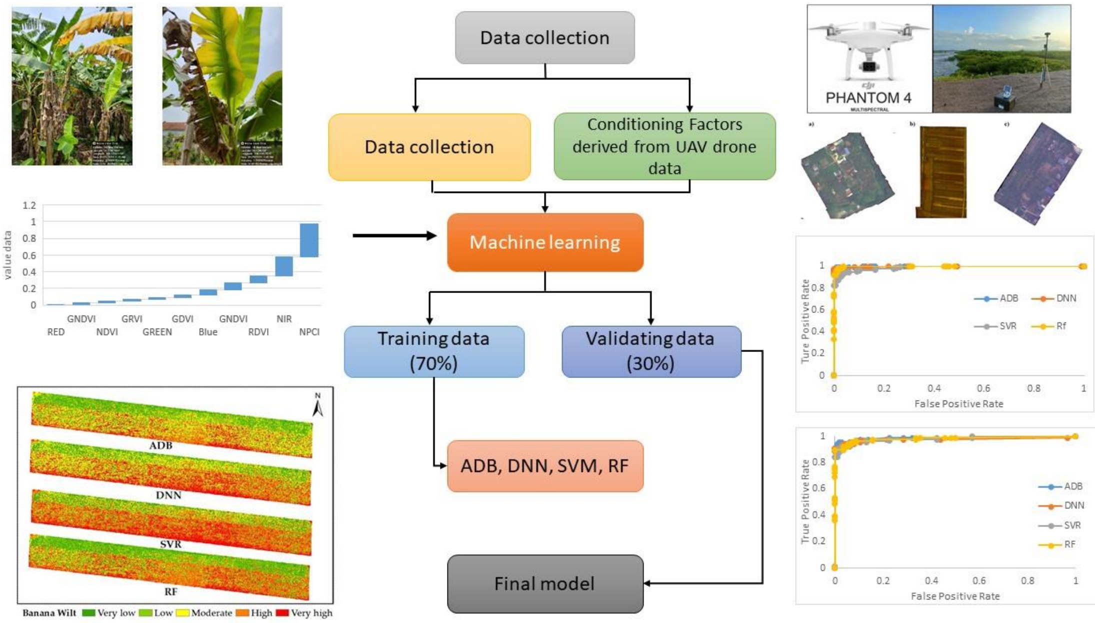

Fig. 3. Methodology used for the banana reigns wilt in this study.

2.4.1. Random Forest

Random Forest is a powerful ensemble learning technique widely used for classification and regression tasks. It operates by constructing multiple decision trees from random subsets of data and aggregating their predictions, which improves accuracy and reduces overfitting. This method is particularly effective at handling unbalanced data sets and missing values, making it a preferred choice in various domains. Random Forest has been successfully applied to predict student dropout rates, optimising its parameters through Grid Search to improve predictive accuracy (Kumar, Kothiyal et al. 2024). By analysing large educational datasets, it identifies at-risk students, allowing timely interventions to enhance retention and academic success. In lung cancer diagnosis, Random Forest achieved an accuracy of 78% by effectively modelling complex data, thus supporting early detection efforts (Benaya 2024). The integration of advanced sampling techniques with Random Forest has shown promise in improving diagnostic sensitivity and specificity. The algorithm is utilised in agrometeorological disaster prediction, outperforming traditional models in classification accuracy and providing information for disaster management (Zhang 2023). Although Random Forest demonstrates significant advantages in various fields, it is essential to consider its computational complexity and the need for substantial data for optimal performance.

2.4.2. AdaBoost

The AdaBoost classifier is a powerful ensemble learning technique that enhances the performance of weak classifiers by combining them into a strong classifier. It operates iteratively, focussing on misclassified instances to improve accuracy. This method has found significant applications in various fields, particularly in medical diagnostics and financial risk analysis. AdaBoost has been integrated with Principal Component Analysis (PCA) and EfficientNet B0 to classify skin lesions, achieving an accuracy of 93% on the DermIS dataset (Gamil, Zeng et al. 2024). Using hot encoding and synthetic minority oversampling, AdaBoost reached a remarkable 99% accuracy in distinguishing between benign and malignant tumours (Chen, Zhou et al. 2024). In financial contexts, AdaBoost demonstrated a recall rate of 91% for high-risk companies, indicating its effectiveness in risk assessment (Zhang and Li 2023). Despite its strengths, AdaBoost can be sensitive to noisy data and outliers, which may affect its performance in certain scenarios. This highlights the importance of data preprocessing and model selection in achieving optimal results.

2.4.3. Support vector machine

Support Vector Machines (SVMs) are powerful supervised learning models widely used for classification and regression tasks across various domains. Their ability to find optimal hyperplanes for separating data points makes them particularly effective in high-dimensional spaces. Recent advancements have further expanded the application of telecommunications technologies, showcasing their versatility in fields such as medical imaging, drug design, and academic integrity. SVMs have been used to identify pseudoreference regions in brain PET scans, significantly reducing variability in quantification between different subjects and scans (Tang, Vanderlinden et al. 2024). The method demonstrated robust performance even with limited data, confirming its utility in clinical settings. In drug discovery, SVMs optimise chemical structures to enhance drug efficacy and safety, aiding in target discovery and protein categorisation (Tang, Vanderlinden et al. 2024). Their application has been critical to addressing challenges related to drug design, including research related to COVID-19. SVMs are also utilised in detecting plagiarism in programming submissions, combining textual and syntactic analysis to improve accuracy over traditional methods (Gandhi, Gopalan et al. 2024). This application highlights adaptability in educational contexts, ensuring academic integrity. While SVMs have shown remarkable effectiveness in various applications, challenges such as computational complexity and the need for large datasets remain. These factors can limit their accessibility and efficiency in certain scenarios and require ongoing research and development.

2.4.4. DNN

Deep neural networks (DNNs) have emerged as a transformative technology within artificial intelligence, enabling significant advancements in various fields. Their architecture, inspired by the human brain, allows for the modelling of complex relationships in data, making them particularly effective in applications such as computer vision, natural language processing, and robotics. DNNs are used to automate weed classification, enhancing agricultural efficiency by distinguishing between harmful species and native vegetation with 90.5% accuracy (Singh, Singh et al. 2024). Recent innovations in DNN architectures, such as CNNs and auto encoders, have expanded their applicability in diverse domains, including natural language processing and social network analysis (Praveena and Vivekanandan 2021). DNNs exhibit superior pattern recognition capabilities and computational speed, making them suitable for real-time applications (Song and Chen 2022). While DNNs have shown remarkable potential, challenges such as complexity and the need for large datasets remain significant hurdles in their widespread adoption. However, ongoing research continues to address these issues, paving the way for future advancements in artificial intelligence (Liu, Wang et al. 2017).

2.4.5. Accuracy Assessment

In this study, we used the statistical indices RMSE, MAE, and AUC to evaluate the precision of the banana reigns wilt recognition model. These indices were calculated using the following equations: Eq. (8), Eq. (9), Eq. (10).

$$\boldsymbol{AUC = \sum TP + \sum \frac{TN}{P} + N} \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_j)^2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | Y_i - Y_j | \tag{10}$$

3. RESULTS

3.1. Statistical Characteristics of the Samples

The selection of appropriate factors plays an important role when using data-driver models in general and machine learning models in particular. These models mainly depend on the statistical characteristics of the sample analysis. In this study, the random forest was used to select appropriate factors for the recognition of the banana reign wilt detection model. Based on the statistical characteristics of the sample analysis, the RF model assigns weights to each conditioning factor; the higher the value of the factors, the greater their importance. In this study, NPCI is the most important factor with an RF value = 0.39, followed by the NIR factor with a value of 0.23, RDVI with a value of 0.09, and GNDVI with an RF value of 0.08. The two factors GNDVI and RED affect the model the least, with values of 0.016 and 0.011, respectively. In general, all conditioning factors in this study directly influence the detection ability of recognition of banana reign wilt (**Fig. 4**).

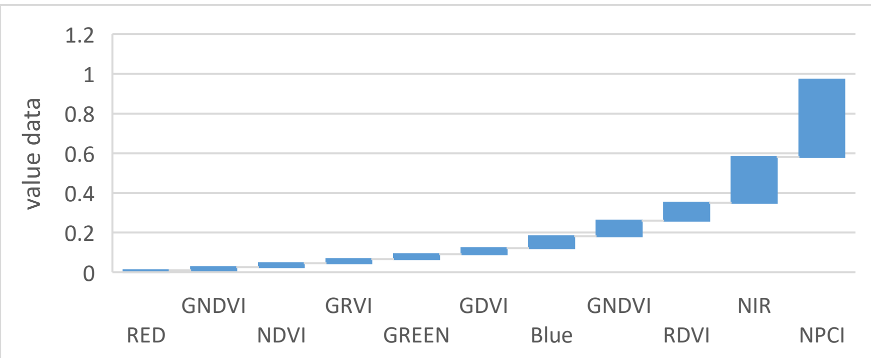

Fig. 4. The importance of data value for the machine learning model.

3.2. Model Performance Assessment

Fig. 5 shows the performance of the models proposed in this study using the AUC value. The results highlighted that the ADB model was superior to the other models with the AUC value of 0.99, followed by DNN with the AUC value of 0.989, RF with the AUC value of 0.985 and SVR with the AUC value of 0.96, respectively, in terms of training data. For the validation data, the ADB model continues to outperform the other proposed models with the AUC value of 0.97, followed by DNN with the AUC value of 0.96, RF with the AUC value of 0.95 and SVM with the AUC value of 0.948.

In general, the ADB model was more accurate than the other models in both training and validation data.

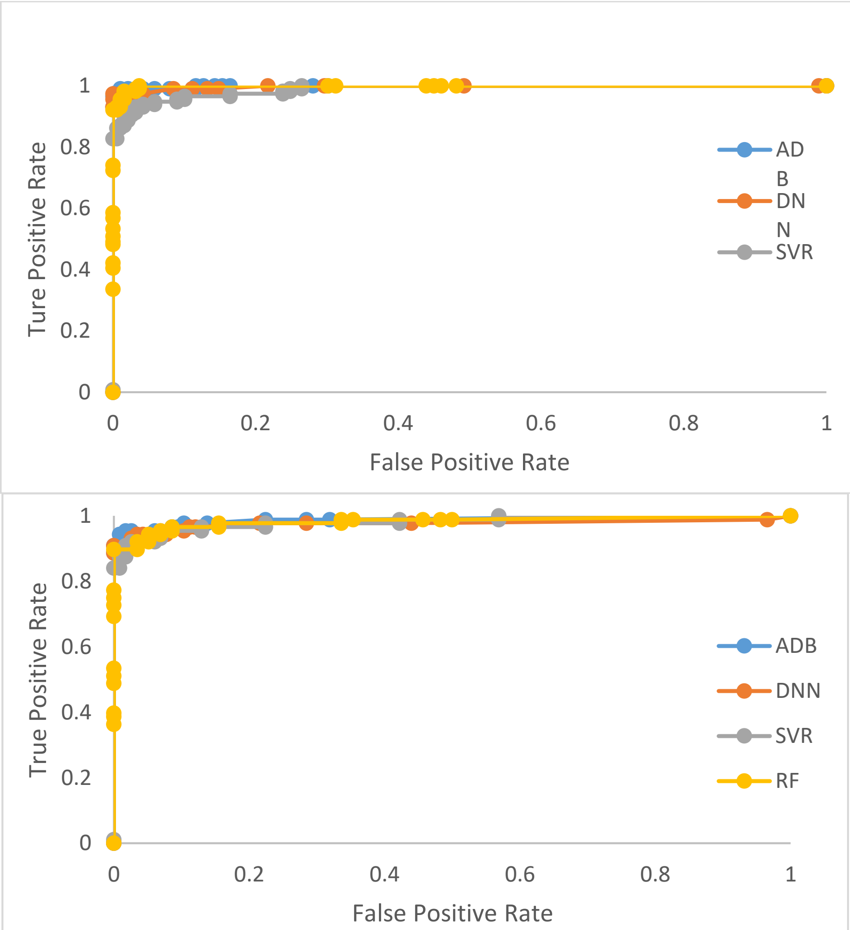

Fig. 5. AUC value for the training data set (top) and the validation data set (bottom).

In addition to the AUC value, this study used other statistical indices such as RMSE and MAE to evaluate and compare the performance of the proposed models. In terms of training data, the ADB model was more accurate than the other three models in predicting wilt with RMSE value of 0.28 and an MAE value of 0.15. A little inferior to the ADB model, the DNN model was second with RMSE and MAE values of 0.3 and 0.17. The RF model was third with RMSE and MAE values of 0.31 and 0.22. Finally, the SVM model was fourth with RMSE and MAE values of 0.35 and 0.25. For the validation data, the ADB model continued to be superior to other proposed models with RMSE and MAE values of 0.29 and 0.17. The DNN model was second with RMSE and MAE values of 0.33 and 0.29. The RF and SVM model was in the third and fourth class with RMSE and MAE values of 0.37 and 0.25 for the RF model and 0.39 and 0.29 for the SVM model (**Table 1**).

Table 1.

RMSE, MAE, AUC values for ADB, DNN, RF, and SVM models.

	Training dataset			**Validating dataset**		
	RMSE	**MAE**	**AUC**	**RMSE**	**MAE**	**AUC**
ADB	0.28	0.15	0.99	0.29	0.17	0.97
DNN	0.3	0.17	0.989	0.33	0.19	0.96
RF	0.31	0.22	0.985	0.37	0.25	0.95
SVM	0.35	0.25	0.96	0.39	0.29	0.948

3.3. Classification results

Fig. 6 shows the spatial distribution map of the areas of banana leaf wilt disease established by ADB, DNN, RF and SVM models. The severity of the disease is divided into 5 levels based on the natural break natural method. Very low (dark green), low (light green), medium (yellow), high (orange), and very high (red). Based on this map, it can be seen that the reigns of wilt banana disease in the study area is unevenly distributed. Specifically, areas with high and very high disease severity are mainly concentrated in the south and the edges of banana gardens, while areas with low and very low disease severity are concentrated in the north.

The reason for this distribution may be related to humidity, nutrition, or poor drainage conditions in the South compared to the North. Furthermore, the edges of banana gardens are often at higher risk due to exposure to external disease sources or inadequate care conditions. Plant density and canopy cover can also influence the spread and severity of wilt disease.

In general, the spatial distribution map of banana wilt disease constructed using machine learning models is an effective tool to support farmers in monitoring and caring for crop health more proactively and accurately. The application of this technology not only helps detect and localise the disease early, minimizing damage, but also contributes to improving the productivity and quality of banana plants, towards sustainable agricultural development.

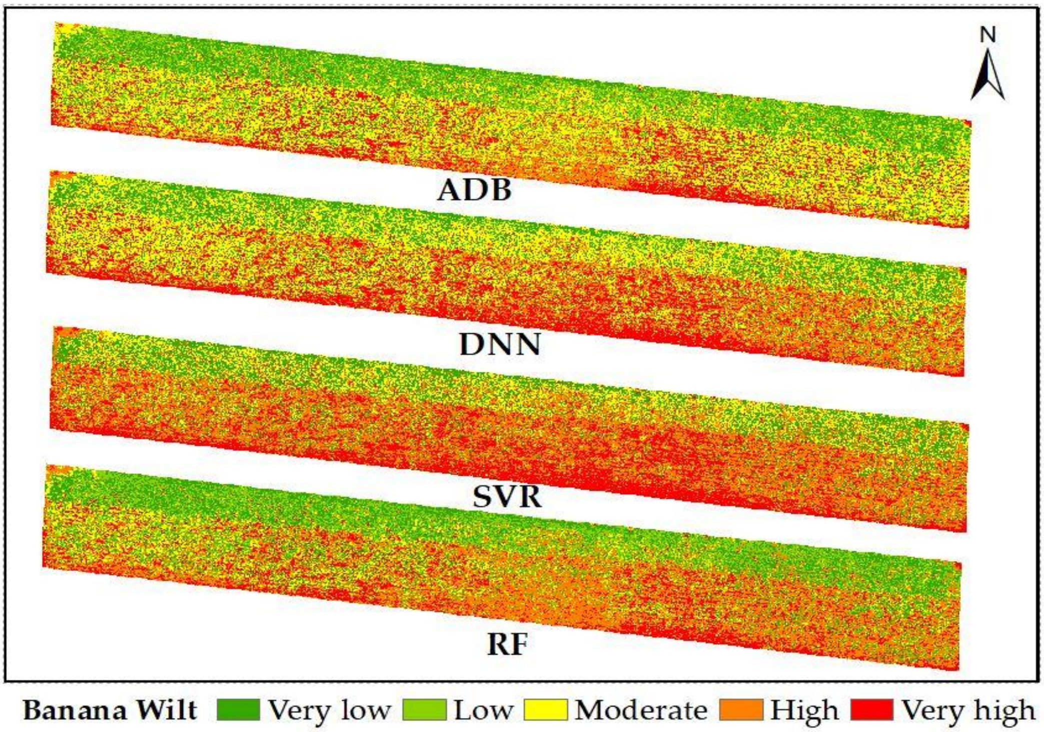

Fig. 6. Banana reigns wilt map produced by ABD, DNN, RF, and SVM.

4. DISCUSSION

UAVs (Unmanned Aerial Vehicles), also known as drones, are increasingly becoming useful tools for large-scale agricultural crop monitoring, especially UAVs with multispectral cameras. Multispectral UAVs allow data collection from multiple reflectance bands in different regions, including the near infrared region (NIR), providing detailed and accurate information on crop health, the environment, factors affecting yield and quality, helping to detect early signs of disease or pests on crops by monitoring changes in colour and light reflectance of crops or growing areas using indices computed from the values of spectral channels on collected UAV images. However, the initial investment cost for UAVs can be high and requires skills to operate and analyse data from UAVs (Ye, Huang et al. 2020). However, multispectral UAVs can be a useful solution to help ensure crop quality and yield, as well as sustainable farmer income for some specific crops with good economic value, including bananas.

The application of machine learning and UAV technology in monitoring plant health in general and Royal Dai Hoang in particular is particularly important, not only helping to detect diseases early but also providing an accurate and effective tool for local authorities and people in monitoring and supervising plant health. This can improve crop productivity and people's income. In addition, this research also plays an important role in the application of advanced technologies in agriculture, especially in rural areas. With the ability to monitor quickly and at a low cost compared to traditional methods, UAV technology and machine learning models can be applied to many other crops in Vietnam, not just the Royal Dai Hoang banana.

Bananas are one of the most produced, traded and consumed fruits worldwide, with more than 1,000 varieties produced worldwide. Bananas provide important nutrients to a wide range of populations, from infants to adults. Globally, the banana sector is particularly important in some less developed and low-income countries, playing a key role in household food security, as well as supporting employment and income generation as a cash crop. The 4th World Banana Forum in 2024 reported that income from banana production could account for up to three-quarters of the total monthly household income of smallholder farmers and generate more than $10 billion in annual export revenue, the majority of which goes to developing countries, including Vietnam. Among Asian countries that grow bananas for export, Vietnam is second in export output after the Philippines (FAO, 2021). Currently, bananas account for 19% of the total fruit growing area with an estimated production of about 2 million tons/year and are among the top 10 major export items of Vietnam. Royal Dai Hoang banana is a typical banana variety grown mainly in Ly Nhan, Ha Nam with a beautiful shape, sweet fruit and characteristic aroma. This type of banana has high commercial value, is especially popular in high-end markets, and is currently on the list of 50 famous speciality fruits of Vietnam. Royal Dai Hoang banana is a crop closely associated with the lives of people in Ly Nhan district, Ha Nam. Thanks to the growth of Royal Dai Hoang Banana, people in Ly Nhan district can increase their income, promote rural economic development and, at the same time sustainably reduce poverty.

Fusarium wilt is a common disease in banana plants because the root system of banana plants is quite shallow, mainly concentrated in the topsoil. This creates favourable conditions for Fusarium oxysporum to easily penetrate the roots and spread in the vascular tissues of the plant. The infected root system prevents the plant from absorbing enough water and nutrients, leading to symptoms of wilt and yellow leaves. Monitoring and detecting Fusarium wilt in banana plants early is extremely important because Fusarium wilt has the ability to spread rapidly through the root system and irrigation water, causing infected plants to slowly wilt and die and spread throughout the entire banana garden, causing great losses in yield and fruit quality. When the disease spreads, treatment and control will be very expensive and ineffective. Therefore, early detection helps reduce treatment costs and avoid having to destroy the entire banana garden. In particular, for the Royal banana tree, the issue of monitoring yellow leaf wilt disease needs more attention because this type of banana is very sensitive to chemicals, so during the care process, farmers cannot use pesticides to prevent pathogens that are harmful to banana trees.

A banana plant with yellow leaf wilt can be detected by analysing changes in the wavelengths of light reflected by the plant using different vegetation indices, including NPCI, RDVI, and GNDVI.

NPCI (Normalised Pigment Chlorophyll Index) is an index that evaluates the chlorophyll content in leaves, helping to detect changes in leaf pigmentation, an important sign of plant health. When banana plants are infected with leaf wilt, the chlorophyll content decreases, leading to changes in leaf color. NPCI helps to detect these changes early, allowing timely intervention to control the disease (Ye, Cui et al. 2020, Zhang, Li et al. 2022). RDVI (Renormalised Difference Vegetation Index) is an improved NDVI index, which enhances the sensitivity to detect changes in vegetation. RDVI is particularly useful in detecting early stages of wilt disease, when physiological changes in plants are not yet apparent. This allows farmers to take preventive measures before the disease spreads (Zhang, Li et al. 2022). GNDVI (Green Normalised Difference Vegetation Index) focusses on the blue and near-infrared wavelengths, which assesses the health of plants based on the amount of light absorbed by leaves. GNDVI helps detect early signs of plant stress due to disease or nutrient deficiencies. For banana plants, this index can indicate areas affected by wilt disease, helping farmers take timely measures (Singh, Singh et al. 2024).

Machine learning models such as ADB, RF, SVM, and DNN have been used effectively to classify and detecting banana leaf wilt disease (Selvaraj, Vergara et al. 2019). The RF model can identify and classify infected banana growing areas based on VI features (Olivares, Vega et al. 2022). SVM and DNN have also been shown to be effective in detecting leaf wilt disease using UAV image data (Selvaraj, Vergara et al. 2020). Among the proposed models, the ADB model has the highest accuracy with an AUC value of 0.98. Because ADB is an easy-to-implement and efficient model by iteratively correcting the mistakes of weak learning models so that they can be modified into stronger ones. In addition, this algorithm allows the use of many different base classifiers, providing high flexibility. In particular, ADB has advantages in solving overfitting problems (Ying, Qi-Guang et al. 2013). The DNN model ranked second with an AUC value of 0.98. Because the neural network structure is flexible, it can be easily changed to suit many different algorithms. It is capable of solving many complex problems with very high accuracy. It is highly automated, self-adjusting and self-optimising (Koziarski and Cyganek 2017, Khalilov, Jumaboyeva et al. 2021). The Rf model ranked third with an AUC value of 0.96, because random forests is considered an accurate and powerful method due to the number of decision trees involved in this process. It does not suffer from overfitting problems (Langsetmo, Schousboe et al. 2023). The SVM model has lower accuracy than the above three models because the SVM model requires high computational resources when the amount of data increases, the results are not accurate if there are a lot of noisy data, and there is no method to automatically determine the kernel of the support vector machine in the case of nonlinear data division (Auria and Moro 2008, Anguita, Ghio et al. 2010).

Machine learning models and UAV technology are becoming an important tools in monitoring plant health in general and leaf wilt disease in banana plants in particular. Machine learning allows for fast and accurate analysis of big data, such as satellite data or data from UAVs to monitor plant health, or leaf wilt. This type of disease causes serious damage to crops. The combination of UAV technology and machine learning models allows for comprehensive and continuous monitoring of plant health, thus providing timely intervention solutions, minimising damage and increasing productivity.

Although this study was successful in building a machine learning model to monitor banana leaf wilt disease, it also has some limitations related to data use. Some of the vegetation indices used, such as NDVI, NPCI, or GNDVI, may not be sensitive enough to some types of disease or stages of disease development, leading to suboptimal detection results. Additionally, the machine learning models used in the study were optimised for banana leaf wilt, but need to be adapted to other crops or different conditions. Future research could integrate data from different seasons and regions to improve the accuracy of models and make them easier to generalize. In addition, although this study used UAV images to provide high-quality data, the volume and uniformity of the data should also be considered because they are affected by factors such as weather, light and environment. This may reduce the classification accuracy. However, in this study, we also used well-known models that can reduce the impact of these factors. In the future, we will try to integrate these models with optimisation algorithms to improve the accuracy of the forecasting model.

5. CONCLUSION

Reigns wilt is one of the common diseases in crops, especially in tropical monsoon countries. Of these, leaf wilt in banana is one of the most common, greatly affecting the productivity and yield of crops. Therefore, monitoring reigns wilt in bananas is one of the important tasks which can help people in isolating the disease, in order to provide timely intervention solutions to minimise damage. The objective of this study was to develop a method based on machine learning and UAV data to monitor reigns wilt bananas. The conclusions of this study are resumed to some point.

Machine learning and UAV data have demonstrated the ability to monitor reigns wilt in bananas. The results of this study can be modified and applied to other plant health monitoring and tracking.

Among the models proposed in this study, the ADB model gave the best results with an AUC value of 0.97, followed by the DNN model with an AUC of 0.96, the RF with 0.95 and the SVM with 0.948. We recommend using the ADB model to monitor and supervise leaf wilt disease in banana plants. The models proposed in this study can be used to monitor and supervise some other crops that may have similar characteristics, such as banana plants.

The results of this study also showed that areas on the edge of banana gardens are at high and very high risk of reign wilt disease. This may be due to the fact that these areas are exposed to more external factors and more limited care conditions than other areas. This provides a scientific basis for people to take interventions to improve farming conditions in these areas.

This research not only contributes to improving the ability to monitor wilting of banana plants, but also opens up the prospect of widespread application of machine learning and drone data in plant health monitoring. This is considered one of the important tasks towards sustainable agricultural development, ensuring people's livelihoods.

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