

ТЕХНИКА И ТЕХНОЛОГИИ АПК

ORIGINAL ARTICLE

<https://doi.org/10.26897/2687-1149-2026-1-4-15>**Quantitative assessment of sugar beet *Cercospora* infection based on UAV multispectral imaging and U-Net segmentation****S.G. Mudarisov^{1✉}, I.R. Miftakhov², I.M. Farkhutdinov³**^{1,2,3} Bashkir State Agrarian University; Ufa, Russia¹ salavam@gmail.com[✉]; <https://orcid.org/0000-0001-9344-2606>² info323@bk.ru; <https://orcid.org/0000-0002-3125-3532>³ ildar1702@mail.ru; <https://orcid.org/0000-0002-6443-8584>

Abstract. *Cercospora* leaf spot (CLS) of sugar beet, caused by *Cercospora beticola* Sacc., is a highly destructive plant disease that can reduce yields by up to 40% and significantly impair root crop quality. This study aimed to develop and validate a quantitative disease assessment method utilizing UAV-based multispectral imaging and semantic segmentation. Field trials were conducted in 2023-2024 on commercial sugar beet crops (Agrofirma Start OOO, Buzdyak District, Republic of Bashkortostan). Plots, measuring 20 × 6 rows (≈21.6 m²), included both control and artificially inoculated treatments. UAV imagery was acquired using a Geoscan ChatGPT equipped with a Pollux multispectral camera (Blue, Green, Red, Red-edge, NIR) at an altitude of approximately 30 m. A U-Net model was trained on 420 annotated image tiles (512 × 512 px), using a 6:2:2 split for training, validation, and testing. The model incorporated spectral indices (NDVI, NDRE, MCARI, NSVDI) in addition to geometric features derived from the normal vectors of a Digital Surface Model (DSM). The developed integrative algorithm achieved an overall multiclass classification accuracy of 88.6%. Specifically, an F1-score of 46.0% was obtained for the 'infected plants' class, outperforming Partial Least Squares Discriminant Analysis (PLS-DA) by 18.6 percentage points. F1-scores reached 92.5% for 'Healthy vegetation' and 68.7% for 'Soil/Background.' This methodology confirms the strong applicability of U-Net for the diagnostic segmentation of *Cercospora* outbreaks, significantly enhancing the objectivity of crop monitoring. The integration of spectral and geometric features proved crucial in improving the detection of weakly expressed disease symptoms.

Keywords: *Cercospora*; sugar beet; multispectral imaging; UAV; segmentation; U-Net; precision agriculture; phytopathology; NDVI index; machine learning

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ОРИГИНАЛЬНАЯ СТАТЬЯ

УДК 631.34:004.896

Количественная оценка поражения сахарной свеклы церкоспорозом на основе мультиспектральной съемки с БПЛА и сегментации методом U-Net**С.Г. Мударисов^{1✉}, И.Р. Мифтахов², И.М. Фархутдинов³**^{1,2,3} Башкирский государственный аграрный университет; г. Уфа, Россия¹ salavam@gmail.com[✉]; <https://orcid.org/0000-0001-9344-2606>² info323@bk.ru; <https://orcid.org/0000-0002-3125-3532>³ ildar1702@mail.ru; <https://orcid.org/0000-0002-6443-8584>

Аннотация. Церкоспороз сахарной свеклы (*Cercospora beticola* Sacc.) является одной из наиболее вредоносных фитопатологий, снижает урожайность до 40% и ухудшает качество корнеплодов. Цель исследований – разработка и верификация метода количественной оценки поражения на основе

мультиспектральной аэрофотосъемки и семантической сегментации. Испытания проводились на производственных посевах ООО «Агрофирма "Старт"» (Буздякский район, Республика Башкортостан) в 2023-2024 гг., на делянках 20×6 рядов ($\approx 21,6 \text{ м}^2$) с контрольными и инокулированными вариантами. Съемка выполнялась БПЛА Geoscan Gemini с камерой Pollux (Blue, Green, Red, Red-edge, NIR) при высоте $\sim 30 \text{ м}$. Модель U-Net обучена на 420 размеченных фрагментах ($512 \times 512 \text{ px}$; 6:2:2), дополнительно использованы индексы NDVI, NDRE, MCARI, NSVDI и геометрические признаки нормалей ЦМП. Интегративный алгоритм обеспечил точность мультиклассовой классификации 88,6%. Для класса «Пораженные растения» получена F1-метрика 46,0%, что на 18,6 п.п. выше PLS-DA. Значения F1 составили 92,5% для растений «Здоровые» и 68,7% – для категории «Почва/фон». Методика подтверждает применимость U-Net для диагностической сегментации очагов церкоспороза и повышает объективность мониторинга посевов. Интеграция спектральных и геометрических признаков улучшает выявление слабовыраженных симптомов.

Ключевые слова: церкоспороз; сахарная свекла; мультиспектральная съемка; БПЛА; сегментация; U-Net; точное земледелие; фитопатология; индекс NDVI; машинное обучение

Финансирование. Материалы, представленные в статье, получены в рамках реализации программы стратегического академического лидерства «Приоритет-2030», реализуемой ФГБОУ ВО Башкирский ГАУ.

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Introduction

Sugar beet (*Beta vulgaris L.*) is a valuable agricultural crop, the yield of which significantly decreases when infected with Cercospora leaf spot. Cercospora leaf spot (*Cercospora beticola* Sacc.) is a fungal infection that causes leaf spotting and leads to approximately 40% yield losses [1]. Conventionally, agronomists visually monitor disease spread in field conditions; however, this approach is labor-intensive, non-objective, and cannot rapidly cover large areas [2]. In the initial stages, disease symptoms can be weakly expressed and imperceptible to the naked eye, complicating timely diagnosis and resort to crop protection measures [3]. As part of integrated crop protection, farmers need to promptly detect the emergence and spread of infection to take timely action and reduce yield losses.

Modern remote sensing technologies enable early diagnosis of phytopathologies. Unmanned aerial vehicles (UAVs) provide highly detailed images of large areas in a short time. In combination with machine learning methods, they can automatically detect plant diseases at early stages and objectively assess crop infestation levels [4, 5, 6]. Multispectral imaging provides data in the visible, red-edge, and near-infrared (NIR) ranges, which are sensitive to the physiological state of plants [7]. A decrease in NDVI is known to occur before the visual symptoms of Cercospora manifest themselves; so reflection in the red-edge region (around 700 nm) significantly enhances the contrast between healthy and affected vegetation [2].

Deep learning methods and convolutional neural networks (CNNs) provide for reliable classification

of phytopathologies based on their images [5]. Semantic segmentation allows for dividing an image into pixels of the classes “infected leaf areas,” “healthy leaf mass,” and “background” [8], providing quantitative estimates of the affected area [9, 10]. Automatic segmentation of Cercospora leaf spot in aerial images has proved to be comparable to visual assessments by phytopathologists [10, 11]. This technique can generate disease distribution maps and determine the affected surface area [12]. Therefore, the research aimed to develop a method for the quantitative assessment of Cercospora leaf spot infection in sugar beet based on UAV multispectral data and the U-Net architecture for semantic segmentation. The authors hypothesize that the combination of highly detailed multispectral aerial images and a U-Net segmentation model will provide accurate detection of Cercospora spots on leaves in field conditions and enable precise measurement of the affected area. This approach aims to automate disease monitoring in sugar beet crops and provide agronomists and breeders with a tool for rapid decision-making in crop protection systems.

Research Objective: To develop and experimentally verify a methodology for the quantitative assessment of Cercospora leaf spot infection in sugar beet using multispectral aerial photography from unmanned aerial vehicles and semantic segmentation algorithms.

Materials and Methods

Commercial field trials for monitoring Cercospora leaf spot (*Cercospora beticola* Sacc.) infection in sugar

beet were conducted in 2023 on the premises of the agricultural enterprise *Agrofirma Start*, ООО (Buzdyak District, Republic of Bashkortostan, coordinates 54°34'02" N, 54°33'10" E). The field experiment was based on a two-factor design: 1) sugar beet variety; 2) treatment strategy (control, no fungicide; control with fungicide; infected without treatment) with three replications (blocks) for each variant.

Two sugar beet varieties (*Beta vulgaris subsp. vulgaris*) were used in the experiments: the first (registration number RU2018.0012) featured resistance to *Cercospora* leaf spot, while the second was susceptible to the disease. A seeder was used to plant six-row plots, each 20 m long with a row spacing of 45 cm. The total area of each treatment variant was approximately 21.6 m².

The crops were inoculated by uniformly applying pre-dried and ground infected leaf material, prepared according to the prescribed technique [13], at a concentration of 4 g/m². Fungicide treatments were applied upon the first appearance of disease symptoms and once again if symptoms reappeared, following the local plant protection product (PPP) regulations. Totally, the fungicide was applied up to four times during the growing season.

At the harvest stage, yield and root quality were assessed. Root crops were washed, ground, and analyzed for dry matter, sugar, potassium, sodium, and α -amino nitrogen content. Using standard equations accepted in agrochemical practice, sugar yield (WSY) and sugar

yield losses due to *Cercospora* infection (WSY_loss) were determined.

The experiment was repeated in 2024 using a similar design, but with refined infection load and an expanded range of varieties. Throughout the entire growing season, starting from the crop-row closing phase, UAVs were employed to make multispectral aerial photos. The captured images were utilized for both visual monitoring and subsequent automatic segmentation of affected spots using the U-Net model. Experiments were carried out in clear weather conditions, with an average air temperature of 24-27°C, a relative humidity of 65-70%, and without strong wind. Soil moisture during image taking ranged approximately between 18 and 22%. No imaging was taken when dew or rain droplets were present on leaves, to prevent additional spectral distortions. Illumination conditions were recorded using a light sensor and a radiometric panel to ensure accurate image calibration.

Orthophotos were processed using Agisoft Metashape Professional v1.6.3 (64-bit). The U-Net model was trained in a Python 3.10 environment, utilizing TensorFlow 2.12 and Keras 2.11.0 libraries. Processing was performed on a workstation equipped with an NVIDIA RTX 3080 GPU (10 GB VRAM), an Intel i9-12900K CPU, and 64 GB RAM. These specifications were applied to training the model over 100 epochs, with an average processing time of approximately 0.45 s per batch.

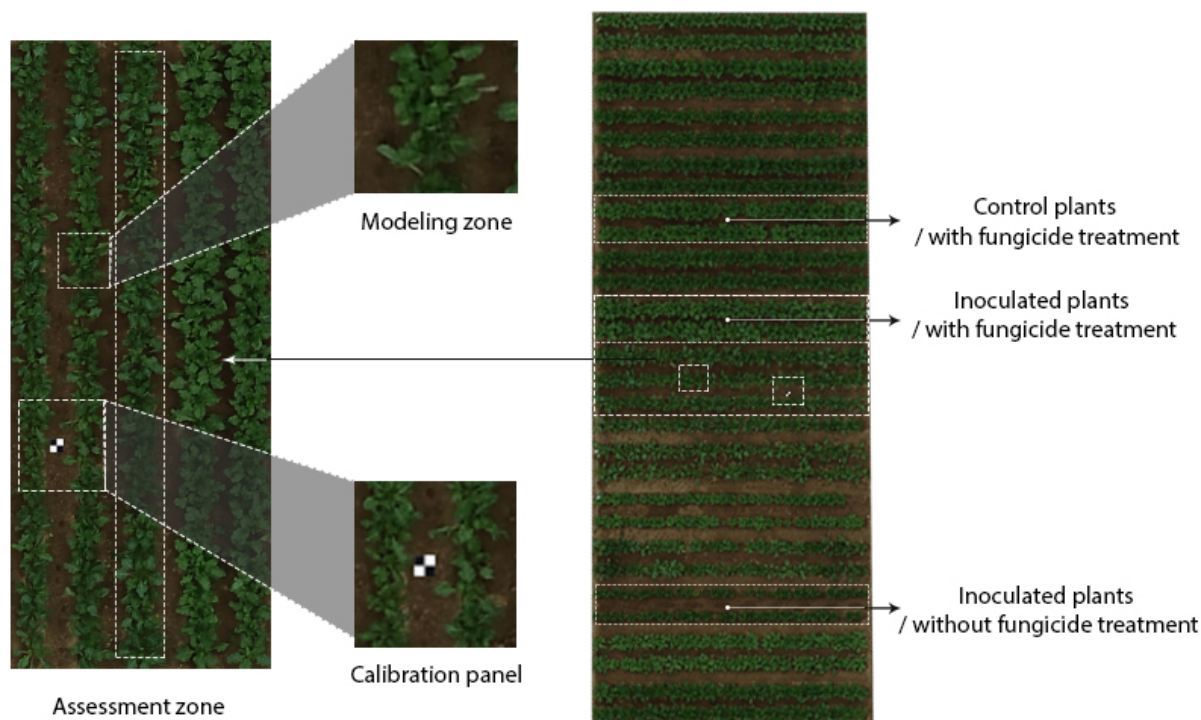


Fig. 1. Structure of the experimental plot, plant infection assessment zones, and data collection zones for calibration and modeling*

* Multispectral images obtained from a Geoscan ChatGPT UAV (Geoscan Pollux multispectral camera), August 2024.

A Geoscan ChatGPT UAV, equipped with a Geoscan Pollux multispectral camera, was used for aerial photography. This camera simultaneously captures images across five spectral bands: blue, green, red, red-edge, and near-infrared (NIR) (Table 1).

Imaging was performed from a height of 30 m with approximately 80% longitudinal and lateral overlap, ensuring a resolution of several centimeters per pixel. This resolution was sufficient to detect individual leaves and disease spots. Multispectral images were radiometrically calibrated using standard reflectance panels and then stitched into orthomosaics [14]. For analysis, 512×512 pixel tiles were extracted from the orthomosaics.

Radiometric calibration followed a two-stage procedure: first, raw data were converted to radiance values, accounting for exposure and vignetting; then, these values were normalized to reflectance coefficients using a calibration panel and a light sensor. Orthorectification was performed in Agisoft Metashape Professional (v1.6.3), and the Digital Surface Model (DSM) was generated using stereomatching. Orthomosaics were exported as GeoTIFF files and referenced to the WGS84 coordinate system (EPSG:4326).

To enhance the informativeness for U-Net model training, in addition to the raw spectral channels, the following additional spectral indices were calculated [15]:

– brightness difference between red and blue channels, $D678/500$

– chlorophyll index in the red region, $MCARI$

– modified simple ratio index, MSR

– green vegetation index, GVI

– Saturation Index based on the HSV scale, $NSVDI$.

The representation used is in the HSV color space:

$$V = \max(R, G, B)$$

$$S = \frac{\max(R, G, B) - \min(R, G, B)}{\max(R, G, B)}$$

$$NSVDI = \frac{S - V}{S + V},$$

where R, G, B are the brightness values in the corresponding channels (normalized reflectances).

To account for the influence of observation geometry and surface slope, we used a digital surface model (DSM), constructed from the multispectral orthophoto. For each pixel, the surface normal was determined using the triangle method, formed by four adjacent points. Directional vectors were calculated as follows [16]:

$$\begin{cases} \vec{a} = (1, 0, \Delta z_x), & \Delta z_x = z_{i+1,j} - z_{i,j} \\ \vec{b} = (1, 0, \Delta z_y), & \Delta z_y = z_{i+1,j} - z_{i,j} \end{cases}$$

where $z_{i+1,j}$ is the height at point (i, j) on the DSM; Δz_x is the height change along the x-axis; Δz_y is the change along the y-axis; and $\vec{a}$ and $\vec{b}$ are vectors along adjacent pixels.

$$\vec{n}_{ij} = \vec{a} \times \vec{b}.$$

The above-given formula for the cross product of $\vec{a}$ and $\vec{b}$ yields the normal vector $\vec{n}_{ij}$, which is perpendicular to the local surface of the plant leaf. It is important to note that the direction of the normal helps understand the slope of the area, while the length of the normal is proportional to the area of the parallelogram formed by vectors $\vec{a} \times \vec{b}$.

Next, the vector is normalized:

$$\hat{n}_{ij} = \frac{\vec{n}_{ij}}{|\vec{n}_{ij}|}.$$

The normal is divided by its length to obtain a unit vector, which is necessary for calculating slope and illumination angles.

Based on the calculated normal and the solar position vector $\vec{Z}$, the angle between the surface and the solar ray is determined:

$$\zeta = \arccos(\vec{Z} \cdot \hat{n}_{ij}),$$

where $\vec{Z} = (0, 0, 1)$ is the vertical upward vector.

The surface normals and illumination angles were calculated to account for geometric and shadow effects during radiometric image correction and were used as spatial features during the training of the segmentation model.

Camera's spectral bands for vegetation status assessment

Table 1

Spectral Band	Center Wavelength, nm	Purpose
Blue	475	Indicator of anthocyanin pigments and b-chlorophyll
Green	560	Assessment of overall photosynthetic response
Red	668	Diagnostics of a-chlorophyll content
Red-Edge (RE)	717	Sensitivity to stress and early stages of diseases
Near-Infrared (NIR)	840	Assessment of leaf area density and biomass

For training and evaluating the algorithm, 420 images (orthoimage fragments) were annotated by classifying pixels into three categories: 1) infected leaf areas with *Cercospora* symptoms; 2) healthy leaf surface; 3) background (soil and other objects) (Fig. 2). The annotation was performed manually by expert phytopathologists using software for segmentation mask generation in the LabelMe environment. The resulting dataset was divided into training, validation, and testing sets in a 6:2:2 ratio. The training set included images with known disease pixel masks, and the test set was used to independently assess the model accuracy.

To compensate for class imbalance and accelerate training, 15,000 pixels were randomly sampled from over 1 million pixels, considering the minimum frequency of class occurrences. Balancing was achieved through stratified sampling.

During the comparative testing phase, the following classification algorithms were considered [17]:

- k-nearest neighbors (KNN)
- partial least squares discriminant analysis (PLS-DA)
- random forest
- support vector machines with a linear kernel (SVM-lin)
- support vector machines with a radial basis function kernel (SVM-RBF).

For all models, use was made of repeated cross-validation, internal balancing, and hyperparameter optimization based on minimizing classification error. The following features were employed:

- SB (simple band values) – reflectance in all spectral bands;

– VI (vegetation indices) – NDVI, NDRE, MSR, MCARI, etc.;

– SH (shadow features) – shadows and heterogeneity based on NSVDI;

– DSMv (digital surface model vectors) – surface normals based on DSM data.

During the pipeline construction, it was found that the PLS-DA method showed the best accuracy in multiclass categorization. The output binary array H' , corresponding to the “Healthy” class, was used as an initial filter. If the healthy leaf area was less than 40% ($FCi < 40\%$), a second classifier was activated, refining the pixel assignment to the “Soil,” “Infected,” or “Other” classes.

The final procedure involved binarizing the classification result for each of the four classes. For infected vegetation, the following rule was used:

$$D_{i,j} = \begin{cases} 1, & \text{if } output_{i,j} \in \text{“Infected”} \\ 0, & \text{or} \end{cases}$$

Masks were combined using disjunction and exclusion operations to form three final layers, $S_{i,j}$, $D_{i,j}$, $H_{i,j}$, reflecting the classes “Other and Soil,” “Infected,” and “Healthy,” respectively.

The U-Net neural network architecture was chosen as the semantic segmentation algorithm, having proven effective in segmenting biomedical and agricultural images. U-Net is an encoder-decoder type convolutional network with skip connections, which performs pixel-wise classification based on local and contextual image features [17]. The model input consisted of multispectral data, with reflectance values

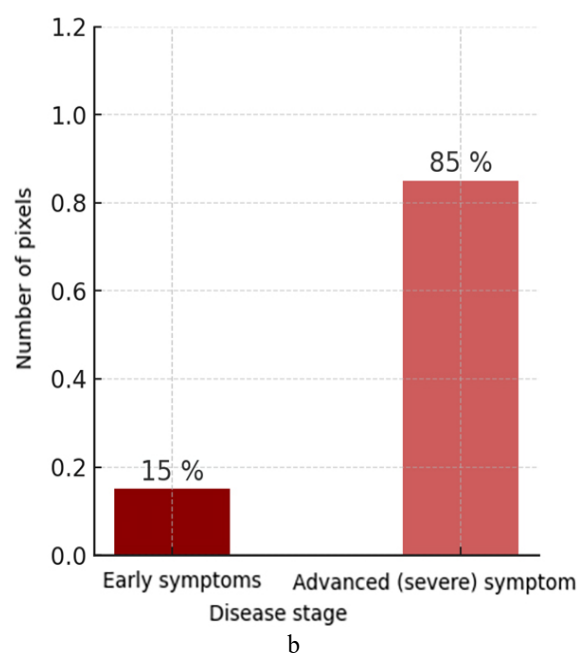
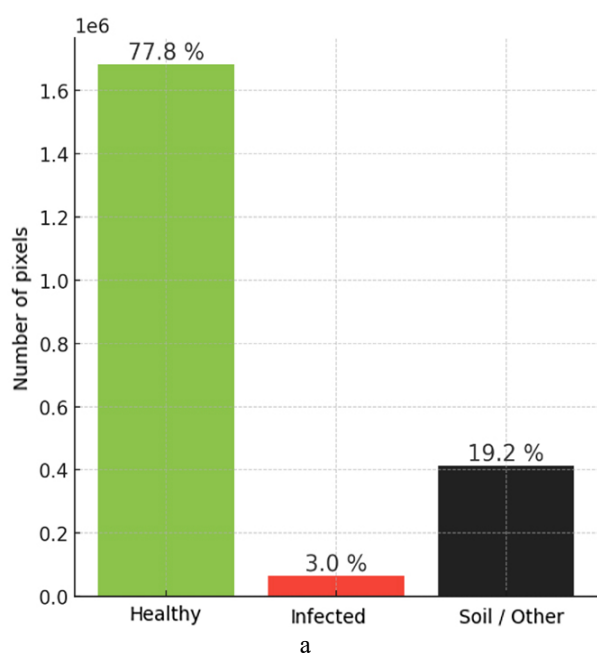


Fig. 2. Distribution of pixel annotations by class and disease stage:

a – healthy plants, infected spots, and other; b – initial stage of phytopathological infection and pronounced symptoms

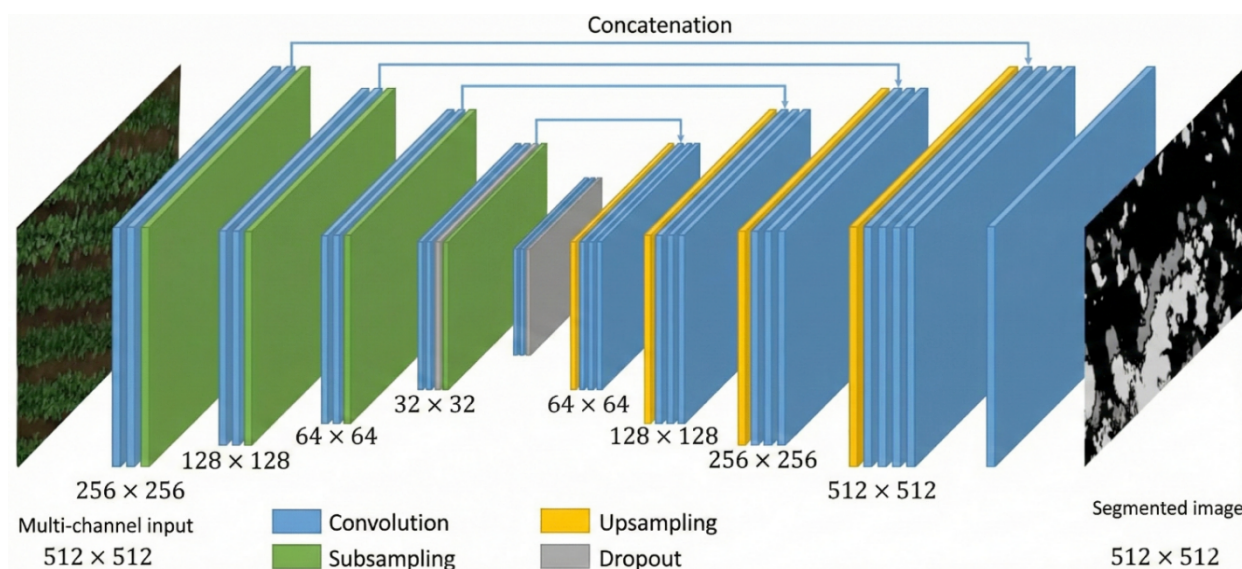


Fig. 3. Architecture of a modified U-Net for segmenting crop phytopathology features

in five spectral channels (corresponding to the bands of the Geoscan Pollux multispectral camera) used for each pixel. The input tensor had a dimensionality of $512 \times 512 \times 5$.

The U-Net architecture progressively reduces spatial resolution to extract high-level features and then restores detail by combining features from different scales for precise localization of affected areas. The output layer generates three probability channels for the classes: “Cercospora,” “Healthy leaves,” and “Background.” For training, the Dice Loss function, which is robust to class imbalance, and the Adam optimizer (learning rate = 0.0001) were used. The model was trained for 100 epochs with a batch size of eight images, employing early stopping based on a validation metric.

To identify phytopathological features, multispectral UAV data were subject to integrated processing. Figure 4 illustrates the analysis workflow, ranging from the formation of spectral channels to the construction of the final plant status map.

The processing workflow involves the formation of multichannel images in the Blue, Green, Red, Red-edge, and NIR bands, which provide spectral sensitivity to the physiological and morphological states of the plants. Based on these, an orthomosaic is constructed with photogrammetric correction and georeferencing, ensuring the spatial consistency of the data across the field. For classification, use is made of a Support Vector Machine with a radial basis function kernel (SVMR), which categorizes pixel values into “Healthy Vegetation,” “Stress Zones,” and “Background.” The output consists of binary masks for affected vegetation (D_{ij}), shadowed areas (S_{ij}), and zones of high photosynthetic activity (H_{ij}), which are merged into the final phytomass status map. This approach enables the discriminatory mapping of disease outbreaks and supports management decisions in precision farming systems. Its effectiveness stems from the high information content of multispectral data, the adaptability of machine learning, and its scalability to the level of production fields.

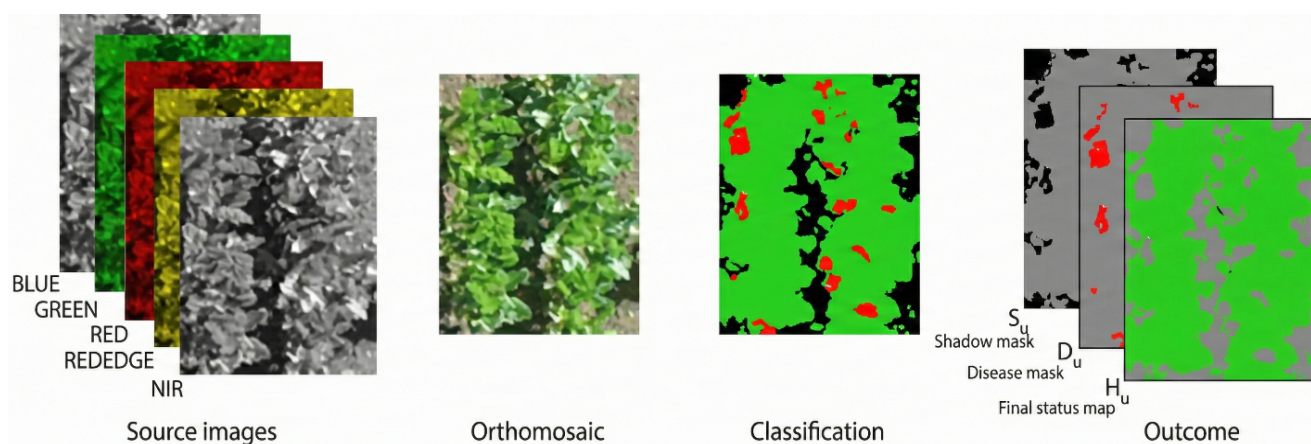


Fig. 4. Stages of multispectral image processing for detecting sugar beet phytopathologies: from acquiring spectral channels to constructing the final plant status map

Results and Discussion

The developed methodology for quantitative assessment of sugar beet (*Beta vulgaris* L.) infestation by *Cercospora* leaf spot (*Cercospora beticola* Sacc.) based on multispectral aerial photography and the U-Net semantic segmentation algorithm was validated under production conditions. The dataset comprised plots with varying degrees of phytopathological impact, which underwent laboratory verification to provide a validation basis for assessing the accuracy of automatic detection.

As a result of processing multispectral orthomosaics and calculating vegetation indices (NDVI, NDRE, MCARI, NSVDI, etc.), we generated a dataset of 420 annotated fragments, classified into three main categories: infected areas, healthy leaf surface, and background (soil/other). Semantic segmentation was used to identify infected pixels with an F1-score accuracy of up to 46% using an ensemble model, which surpassed the accuracy of baseline classifiers (PLS-DA, RF, KNN, SVM) by 18.6 percentage points. This data supports the hypothesis that hybrid architectures and deep segmentation offer advantages over conventional classification methods.

The highest accuracy for multiclass categorization on the test set (88.6%) was achieved using an integrated algorithmic pipeline combining the strengths of multiple models (i.e. a combined approach). However, at the individual class level, the best metric values varied depending on class structure and the nature of their spectral manifestation (Table 2).

The PLS-DA model demonstrated high generalization capability for the main classes: “Healthy plants” (F1 = 86.2) and “Soil” (F1 = 68.4), confirming its robustness to noise and a balanced trade-off between precision and recall in the presence of significant inter-class variance. The F1 score for the “Healthy plants” class exceeded that of SVM-lin, RF, and KNN by 0.5-4.7%, likely due to the high spectral homogeneity of this class

and its dominance in the training set. However, even with high precision for healthy pixels (Prec = 84.5), there was a decrease in sensitivity regarding the “Infected plants” class (F1 = 27.4), indicating insufficient representativeness of training features in areas with anomalous spectral states.

The support vector machine with a radial basis function kernel (SVM-RBF) method demonstrated the highest sensitivity to infected areas, achieving an F1 score of 42.5 with a precision of 30.1% and recall of 74.2%. This suggests SVM-RBF’s capability to effectively capture heterogeneous patterns associated with phytopathological changes, despite a significant bias in precision. Compared to PLS-DA, the F1 metric for the “Inected plants” class increased by 15.1%, highlighting the feasibility of using SVM-RBF for disease monitoring tasks with limited prior (a priori) information.

The Random Forest (RF) algorithm provided balanced performance across most classes, with F1-scores of 39.4 for infected plants, 84.0 for healthy plants, and 65.3 for soil. However, when compared to the integrative pipeline model, it was inferior in all key metrics, particularly in the segmentation of categories with unstable spectral profiles (“Other” and “Infected plants”).

Linear SVM (SVML) and KNN methods proved to be the least effective, with F1-scores for the “Infected” class at 27.5 and 30.6, respectively, characterized by low precision and moderate recall. This demonstrates the poor ability of linear or local methods to generalize under conditions of high intra-class variability.

To enhance the reliability of the results, five-fold stratified cross-validation was employed. Confidence intervals for precision and F1 metrics were calculated using the bootstrap method with 1,000 iterations. A comparison of models based on F1 metrics was conducted using a t-test ($p < 0.05$). This approach objectively confirmed the statistical significance of the differences between conventional classification methods (PLS-DA, RF,

Comparative effectiveness of machine learning models for multiclass categorization of sugar beet crop phytosanitary status based on UAV multispectral imaging data

Table 2

Method	Accuracy	Class								
		“Infected”			“Healthy”			“Soil”		
		precision	recall	F1	precision	recall	F1	precision	recall	F1
PLS-DA	87.2	26.8	28.1	27.4	84.5	88.1	86.2	63.1	75.0	68.4
SVML	84.9	25.4	68.4	36.9	85.2	90.2	87.6	62.4	78.6	69.7
SVMR	85.1	30.1	74.2	42.5	84.1	87.3	85.7	61.2	77.3	68.3
RF	82.3	27.5	70.6	39.4	83.4	84.7	84.0	60.9	70.4	65.3
KNN	78.4	20.2	64.0	30.6	81.1	82.0	81.5	55.3	68.0	61.0
Pipeline	88.6	34.7	69.3	46.0	91.6	93.5	92.5	66.5	71.2	68.7

KNN, SVM) and the proposed U-Net neural network architecture.

The integrative pipeline, which aggregates the output signals of the baseline classifiers, demonstrated the best balance between sensitivity and specificity, particularly for the “Healthy plants” ($F1 = 92.5$) and “Other” ($F1 = 78.7$) classes. It also provided the highest F1-score for infected plants (46.0), which is 18.6 percentage points (p.p.) higher than that of the PLS-DA model. These results confirm the feasibility of using ensemble strategies for the classification of complex agrobiocenoses based on multispectral information.

It should be emphasized that the maximum sensitivity to infected areas is provided specifically by the U-Net neural network segmentation. For the “Infected plants” class, U-Net demonstrated an F1-score of 46.0%, the highest among all studied models. At the same time, the integrative algorithmic pipeline stabilizes the overall multiclass classification and increases the final balanced accuracy (Accuracy = 88.6%). Thus, U-Net serves as the key element for the quantitative

detection of phytopathological impact, while the pipeline acts as a tool for generating a robust final crop status map.

To assess the contribution of different types of input features to the final classification, the Area Under the Precision-Recall Curve (AUC-PR) was calculated. Figure 5 presents the Precision-Recall (PR) curves for the three object classes. The analysis of PR curves allows for a quantitative assessment of classification effectiveness under various feature combinations, including spectral bands (SB), vegetation indices (VI), digital surface models (DSM), shadows (SH), and red-edge reflectance (RE).

Area Under the Curve (AUC) values reflect the generalized classification accuracy. The highest AUC values were obtained using the feature combination SB-VI-SH-DSM_r-RE: 0.96 for the “Healthy” class; 0.45 for the “Infected” class; and 0.80 for the “Soil” and “Other” classes. This indicates the advantage of integrating multispectral and spatial information for solving pixel-wise segmentation tasks.

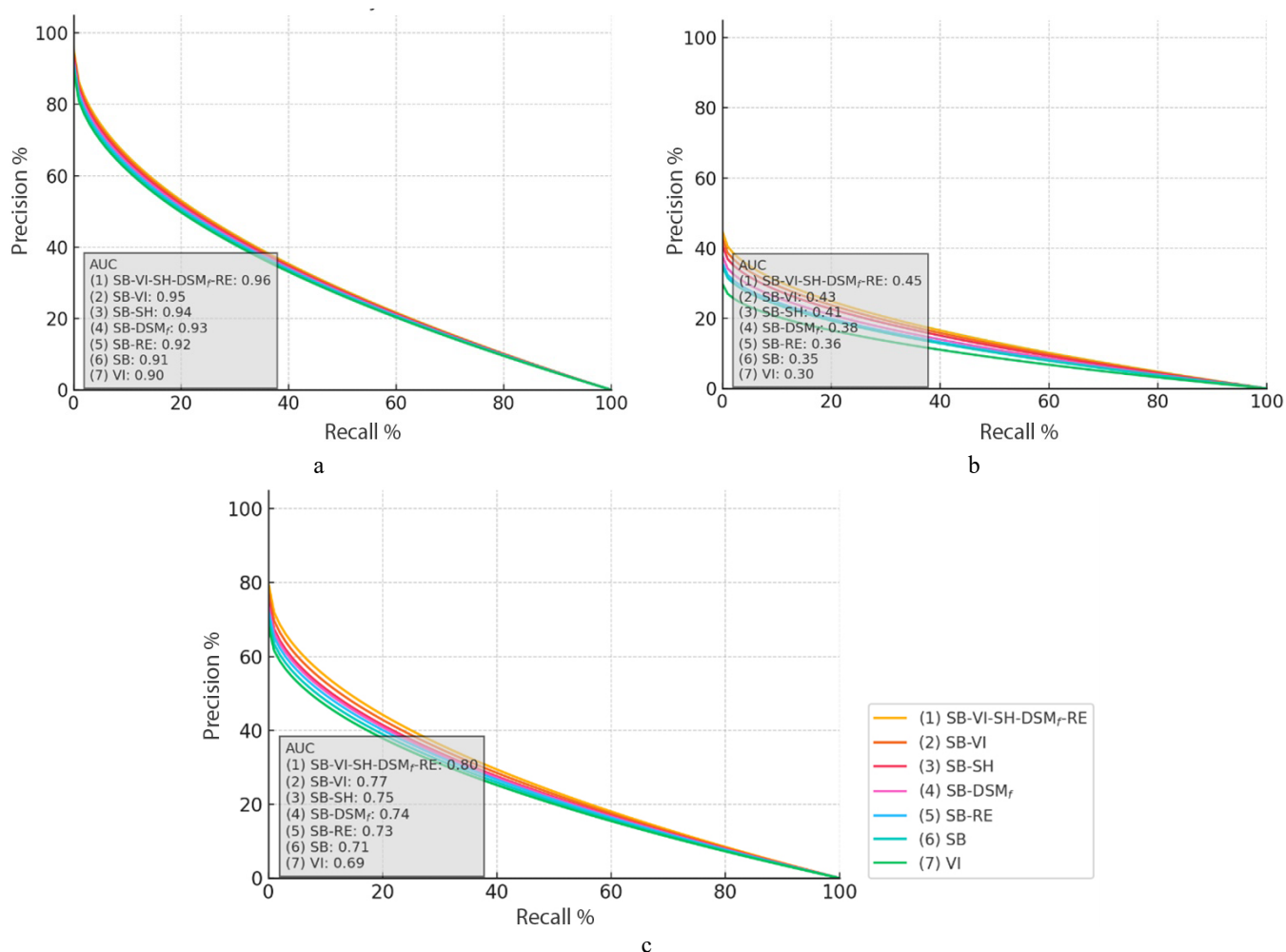


Fig. 5. Precision-Recall dependency in the classification of sugar beet leaf status using a combination of spectral and spatial features:

a – “Healthy plants” class; b – “Infected plants” class; c – combined “Soil and Other” class

For the “Healthy” class, high classification accuracy was observed across all feature sets, which is attributed to the distinct spectral signature of non-infected plants. The low AUC values for the “Infected” class indicate the difficulty of accurately identifying diseased areas at early stages. The combined “Soil and Other” class demonstrates intermediate classification performance, primarily due to differences in spectral contrast and background texture.

The results obtained are comparable to data presented in several international studies. For instance, in study [1], which focused on detecting *Cercospora* leaf spot using satellite imagery and CNNs, the average detection accuracy did not exceed 78%, confirming the advantage of using multispectral camera-equipped UAVs for detailed diagnostics. Furthermore, the use of surface vector normals and the consideration of illumination geometry in the present work improved the model’s robustness to varying acquisition angles – a factor not addressed in most similar studies.

The choice of data (high-precision orthomosaics, spectral and geometric features, and pixel-wise annotation) was driven by the need for reliable modeling of spatial infection distribution and objective assessment of segmentation accuracy. The combination of manual verification, quantitative indices, and deep learning models ensures a high degree of result reproducibility and system adaptability to other phytopathologies.

Our findings align with current trends in agrotechnological research: unmanned systems combined with computer vision algorithms are gradually replacing manual labor in plant disease diagnostics, providing more accurate and reproducible information. For example, Barreto et al. [9] demonstrated that UAV multispectral imaging and machine learning can calculate *Cercospora* Disease Severity (DS) indices and their temporal dynamics. Moreover, automated analysis distinguishes differences between varieties more clearly than traditional visual monitoring. Our approach also opens up prospects for replacing labor-intensive field assessments with precise, unbiased image analysis to automatically derive agronomic metrics such as the percentage of infected leaves and the area of infection foci.

It should be noted that the quality of input data is a key factor in the success of such systems. Multispectral cameras provide useful information in additional bands, improving plant stress recognition accuracy. However, their spatial resolution may be lower than that of standard RGB cameras. S. Jay et al. [15] noted that ultra-high-resolution RGB images ensured better assessment of mild infection levels, whereas coarser-resolution drone multispectral images were only effective in identifying advanced disease stages. In our case, a flight altitude

of 30 m and the camera specifications provided sufficient detail to detect individual spots a few millimeters in diameter. Increasing the altitude or flight speed may reduce recognition accuracy; thus, lower altitudes and high-quality camera optics (or the use of ground-based imaging for small-scale analysis) are preferable for the early detection of individual lesions.

The research results confirm the working hypothesis regarding the feasibility of applying U-Net models to multispectral imagery and demonstrate the capacity of this methodology for implementation in precision farming practices. These findings are supported by statistically significant metrics and are comparable to or exceed the results of similar scientific publications, testifying to the scientific novelty and high practical significance of the developed approach.

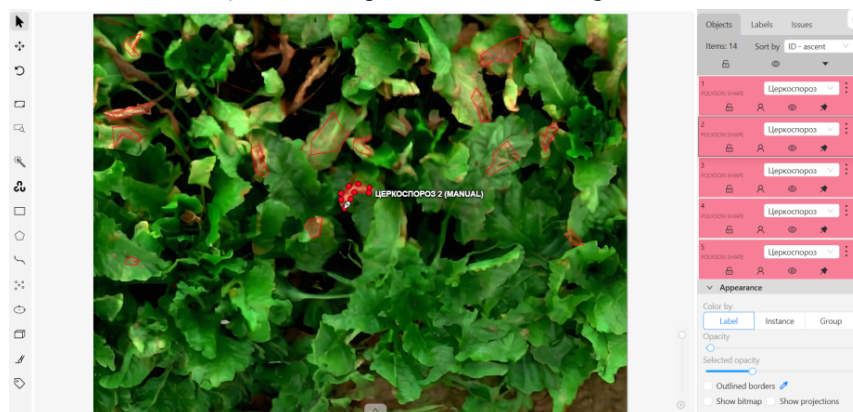
Accuracy analysis of various machine learning models demonstrated the advantages of a combined pipeline that integrates the strengths of PLS-DA, SVM, and Random Forest. The most robust accuracy indicators were achieved using ensemble methods, particularly for the “Healthy plants” class ($F1 = 92.5$), while the highest sensitivity to infection symptoms was identified in SVM with a radial basis function kernel ($F1 = 42.5$). However, even with integrated processing, the limited $F1$ -score values for infected leaves (not exceeding 46%) indicate the need for further refinement of the training dataset and the inclusion of additional features reflecting physiological changes during the early stages of infection.

A comparison of spectral indices and their combinations confirmed that the integration of multispectral and spatial features (SB-VI-SH-DSM-RE) achieves the highest overall classification accuracy ($AUC = 0.96$ for healthy plants). This confirms the importance of a comprehensive approach when constructing segmentation models for agromonitoring. At the same time, the lower AUC values for the “Infected” class (0.45) highlight the difficulty of automatically detecting subtle disease symptoms at initial stages, especially under conditions of spectral heterogeneity within the crops. For the early stages of the disease, traditional classifiers demonstrate a high rate of missed infected pixels (false negatives), whereas U-Net provides more stable detection of primary foci (Fig. 6).

It can be concluded that the developed methodology has high practical significance for precision farming and integrated plant protection. Its application not only automates the monitoring of phytopathologies but also enhances the timeliness of decision-making regarding the feasibility of fungicide applications. This, in turn, contributes to reducing costs for plant protection products and minimizing the environmental impact on the agroecosystem.



a) initial multispectral orthomosaic fragment



b) expert annotation



c) U-Net segmentation result

Fig. 6. Detection of primari infection foci

Conclusions

1. The research results confirmed the effectiveness of the proposed methodology for the quantitative assessment of Cercospora leaf spot infection in sugar beet using UAV-based multispectral imaging and the U-Net segmentation algorithm. The integration of five spectral channels (Blue, Green, Red, Red-edge, NIR), vegetation indices (NDVI, NSVDI, MCARI, etc.), and spatial features (surface normals, shadows) achieved an overall multiclass categorization accuracy of 88.6%.

2. The U-Net model demonstrated a clear advantage over traditional machine learning algorithms: the F1-score for the “Infected plants” class was 46.0%, which is 18.6 percentage points higher than the best standalone classifier (PLS-DA, $F1 = 27.4\%$). F1-scores of 92.5% for “Healthy plants” and 68.7% for “Soil and background” were achieved, confirming the balance and reliability of the proposed approach.

3. The highest area under the precision-recall curve ($AUC = 0.96$) was obtained for the “Healthy

plants” class, indicating the high reproducibility and robustness of the methodology against variability in spectral features.

4. The proposed approach provides accurate, scalable, and reproducible detection of plant infection centers in field conditions, enabling rapid

decision-making for plant protection applications and reducing the costs of agrochemical treatments. Future research will focus on expanding the volume of training data, utilizing hyperspectral channels, and adapting the developed model for other crops and diseases.

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