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Application of unmanned aircraft remote sensing image processing method based on artificial intelligence algorithm in corn growth assessment

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SUMMARY: *This paper proposes a method based on UAV low-altitude photogrammetry and deep learning algorithms for corn crop growth monitoring. During the shooting process, a unified UAV photogrammetry strategy is set to ensure that the obtained images have high spatial resolution, and after pre-processing the original images, a convolutional neural network (CNN) model is utilized to extract features from the images and improve the accuracy of the CNN with the help of the idea of transfer learning. In addition, multi-scale feature fusion and attention mechanism are introduced to allow the model to focus on important location information, and weighted multi-task loss function is used to jointly optimize the multi-objective values such as plant height, leaf area index, and biomass. Experiments show that the method has good real-time performance and scalability while maintaining high prediction accuracy, providing an effective solution for crop monitoring in precision agriculture.*

KEYWORDS: *unmanned aircraft remote sensing; corn growth assessment; convolutional neural network; multi-scale feature fusion*

1 Introduction

Due to the continuous growth of global population, reduction of available arable land area, and intensification of extreme weather changes, food security is facing serious impacts and great challenges, and the assessment of longevity plays an increasingly important role in national agricultural decision-making, international trade adjustment, and food supply security [1, 2]. As the number one crop in China, corn accounts for 38.9% of China's total grain production and is widely used in animal feed, biofuel, starch and its derivatives, which has an important impact on the development of the agricultural industry chain and the national economy [3, 4]. Therefore, researching and realizing efficient and reliable maize growth assessment is crucial to guarantee food security, and it can also provide reference and demonstration for the intelligent cultivation of other crops such as wheat and rice [5, 6]. However, traditional assessment methods are mainly based on manual determination, which is time-consuming, labor-intensive, destructive and with incomplete spatial coverage, limiting the rapid development of dynamic assessment of growth potential.

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In recent years, UAV remote sensing image processing methods have developed rapidly, with significant advantages such as fast information acquisition, rich sensor types, wide spatial coverage, high data resolution, etc. Through data acquisition, image pre-processing, and feature extraction, it can realize the accurate crop growth assessment in continuous time scale, and it has been widely used in maize growth estimation [7-10]. Meanwhile, with the development of artificial intelligence technology, the intelligent application of UAV remote sensing image processing methods in corn growth estimation can be realized by incorporating artificial intelligence algorithms such as deep learning models, which makes the evaluation process achieve high accuracy under the premise of non-destructiveness [11-14].

In this paper, we propose a set of corn growth analysis methods based on UAV aerial images and CNNs, obtaining high-quality aerial images under uniform shooting rules, de-fogging, aligning, and normalizing the acquired images; using CNNs for feature extraction of corn growth information, and at the same time, adding migration learning to enhance the robustness of the network, and designing and realizing cascaded multi-scale pyramid pooling layers and adaptive weighted attention network. The network is allowed to have the ability to focus on the local area as well as extract fine-grained features and global information; the loss function adopts the form of weighted multi-objective regression to jointly optimize the estimation of parameters such as plant height, leaf area ratio and biomass. The method has good real-time performance and scalability while ensuring high accuracy, providing an effective technical solution for crop growth monitoring in precision agriculture.

2 Key technologies

2.1 Remote Sensing

2.1.1 UAV remote sensing technology

In recent years, as the advantages of UAV remote sensing technology in terms of flight flexibility, cost control and image acquisition time have become more and more apparent, its application in the field of agriculture has gradually become one of the most important tools for the modernization of agriculture, and it carries a variety of sensors such as multi-band, ultra-multi-band, and thermal sensing that can simultaneously obtain spatial information in different dimensions. This provides an unprecedented level of data support for fine management in agricultural production. This is because traditional satellite remote sensing data is always affected by factors such as cloud cover and periodicity due to its large area. At the same time, due to the characteristics of the UAV framework such as high mobility and low flight altitude, it is able to monitor high-frequency and high-precision agricultural conditions on the farmland in a suitable time, so the UAV remote sensing can be applied in all aspects of agricultural production. At present, in terms of agricultural remote sensing monitoring, the application of drones has been expanded to the monitoring of crop growth, crop yield estimation, early warning of crop diseases and pests, as well as the investigation of soil fertility distribution, water resource management and other aspects of the specialized application level, forming a more complete process of agricultural remote sensing application technology.

2.1.2 Crop monitoring techniques

In the research on crop monitoring technology, it is found that UAV remote sensing technology can accurately and rapidly obtain crop canopy structure information, quantitatively estimate leaf area index, accurately determine aboveground biomass and other important crop growth factors, and on the basis of obtaining multiband reflectance coefficient, scholars began to try to carry out the operation of vegetation index. Such as the commonly used normalized vegetation index:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \tag{1}$$

where ρ_{NIR} and ρ_{Red} denote the values of feature reflectance in the near-infrared and red light bands, respectively, and there is a highly significant quantitative relationship between this index and key physiological and biochemical parameters, such as crop chlorophyll concentration and vegetation cover.

The use of high-resolution multi-band remote sensing images carried by UAVs to carry out fine growth monitoring of crops such as wheat, rice, corn and other crops has made great progress, and the overall accuracy has reached more than 85%; crop pests and diseases identification has also made certain technical progress, on the basis of fully exploring the changing law of spectral reflectance of the canopy of the crop population, the integration of artificial intelligence technology can accurately determine in advance where pests and diseases will Occurrence of the location, and its positioning analysis, in the process of agricultural production of pests and diseases in a timely and effective treatment to provide scientific and reliable information support. In the soil environment, the spatial distribution characteristics of soil surface temperature collected by UAV-carried thermal infrared sensors and visible and near-infrared remote sensing images can be used to estimate the content of water and organic matter in the soil, thus realizing the spatial dynamics monitoring of soil fertility status, which plays an important role in soil fertilization, irrigation and other aspects.

2.1.3 Growth assessment techniques

Vegetation growth condition is a major research direction of UAV remote sensing applied to the field of crops, and it is also one of the more in-depth research directions at present. Corn is an important field crop and has an obvious growth cycle, and its canopy structure, canopy coverage and plant height changes are all information sources that can be obtained using remote sensing.

With the development of maize reproductive process, there is a certain pattern of change in the reflectivity of its canopy to electromagnetic radiation of different wavelengths from visible light to short-wave thermal infrared electromagnetic waves. In the seedling stage, the overall reflectance of the canopy is higher due to the influence of lower leaf density and greater soil background interference; while in the late stage of nodulation, the increase of leaf area index makes the reflectance of the canopy in the near-infrared region rise sharply, whereas the reflectance of the red light wavelengths will decrease. Based on the above characteristics of spectral properties, modified vegetation indices, such as the soil conditioning vegetation index (SCVI), are proposed for monitoring maize growth conditions:

$$SAVI = \frac{(1+L)(\rho_{NIR} - \rho_{Red})}{\rho_{NIR} + \rho_{Red} + L} \tag{2}$$

From the effect of actual engineering application cases, the method of monitoring maize growth by remote sensing from drones is feasible and effective, and a large-scale experiment in maize growing areas in North America shows that the accuracy of maize plant height prediction based on multi-band information obtained from drone images and supplemented by field measurements can reach 92%. In some developed countries in Europe, early prediction of final maize yields has been achieved through the establishment of a close coupling between maize growth and development models and remote sensing observations, and has reached a level of prediction accuracy that can be used commercially.

2.2 Remote sensing image processing techniques

With the development and optimization of AI-related algorithms, the method of feature information extraction based on remote sensing images has also developed from the initial traditional machine pattern recognition method to the current AI-based deep learning method. Its development and changes have had a profound impact on the field of feature information extraction and have been widely used in the fields of land use/cover change survey and crop growth monitoring.

Convolutional neural network (CNN) is able to automatically extract spatial structure and spectral features from raw pixel data through its unique hierarchical feature learning mechanism. Its mathematical formulation is a composite function of multilayer nonlinear transformation, let the input remote sensing image be $X \in \mathbb{R}^{H \times W \times C}$, H, W, C denote the height, width and the number of spectral bands of the image, respectively, and the output feature maps of the convolution operation of the l th layer can be expressed as:

$$Y^{(l)} = f(W^{(l)} * X^{(l-1)} + b^{(l)}) \tag{3}$$

where $W^{(l)}$ is the convolutional kernel weight matrix of the l th layer, * denotes the convolution operation, $b^{(l)}$ is the bias vector, and $f(\cdot)$ is the nonlinear activation function.

For the classical convolutional neural network architecture, in order to better apply to the field of agricultural remote sensing, multi-scale information integration, self-attention module and residual links are added to the network structure design to enhance the network's ability to deal with the complex background environment of agricultural remote sensing images; The target detection technique is developed from sliding window based target detection to directly utilize deep neural networks to achieve end-to-end target detection, and a two-stage target detection scheme based on Regional Proponent Networks (RPNs) Faster-RCNN model is proposed, which can well deal with the detection of small targets in remote sensing in agriculture. YOLO and SSD, on the other hand, are biased towards real-time, and have been applied in the recognition of agricultural equipment, crop pest and disease spot recognition, and monitoring of farmland infrastructure.

Image segmentation, as the core link of remote sensing data processing, has realized the leapfrog development from simple threshold segmentation to end-to-end semantic segmentation network driven by deep learning. Fully convolutional networks achieve pixel-level dense prediction capability by replacing the fully connected layer of traditional convolutional neural networks with a convolutional layer, and the segmentation loss function usually takes the form of cross-entropy loss:

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \tag{4}$$

where N is the total number of pixels, c is the number of categories, $y_{i,c}$ is the true label of pixel i belonging to category c, and $\hat{y}_{i,c}$ is the model prediction probability.

Since the U-Net model has the encoder-translator framework as well as the hopping connection, it has a great advantage in dealing with small object recognition, and can be used in image segmentation fields such as farmland contour line detection and cultivated land recognition; Support Vector Machines (SVMs)) still perform well in some cases, and the loss function is defined as:

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

The constraints are:

$$y_i(w^T\phi(x_i)+b) \geq 1-\xi_i \tag{6}$$

where $\phi(x_i)$ is the kernel function mapping, C is the regularization parameter, and ξ_i is the slack variable.

Random forest achieves the classification task by integrating the prediction results of multiple decision trees, and shows good generalization ability when dealing with high-dimensional remote sensing data.

3 Design of a methodology for maize growth assessment

3.1 Data acquisition

The designed data acquisition system is based on a representative flat field maize growing area, and several field experiments were carried out. In the paper, a DJM300RTK airplane with a DSLR camera and a MS600Pro multispectral camera were used as the payload equipment, and a total of 8 flights were carried out to photograph the target area during the whole growing season, and the changes in the important stages of maize fertility were basically covered by the acquisition once every 15 days.

The design of this flight program has fully taken into account the requirements of precision agriculture remote sensing monitoring technology: the flight altitude of 120m ensures the ground sampling spacing of about 3cm, and the coverage of a wide range of experimental plots can be accomplished in one flight; the serpentine line back-and-forth flight mode with 80% and 70% of the heading and side overlap can satisfy the requirements of image splicing accuracy. It can provide effective guarantee for more accurate three-dimensional reconstruction. The flight speed of 5m/s can better guarantee the image clarity, while the shooting interval is set to 2s to ensure that a single ground point has multiple images to observe to meet the requirements of post-processing. The relevant parameters of data acquisition using UAV photogrammetry are shown in Table 1. The whole image acquisition system deployment scheme fully considers the demand for rich information dimensions in the process of monitoring maize growth status, and the 20-megapixel CMOS sensor can provide high-definition RGB images for characterizing the appearance of maize canopies as the basis of status identification; the multispectral camera provides five proprietary bands, which include blue (450nm), green (560nm), red (650nm) and red edge (730nm). There is also the 840nm near-external red edge, which was found to be better sensitive to characterize the changes in maize chlorophyll, leaf area index, and biomass after studying the spectral characteristics of the vegetation.

Table 1: Technical Parameter Configuration for Unmanned Aerial Vehicle Data Acquisition

Parameter category	Specific parameters	Set values and instructions
Flight parameters	Flight altitude	120 meters (ground sampling distance 3cm)
	Flight speed	5m/s (to ensure image clarity)
	Course overlap	80% (Ensuring splicing quality)
	Lateral overlap degree	70% (Ensure complete coverage)
Camera parameters	Sensor type	20 million pixel metal oxide semiconductor
	Sensitivity setting	100 (Best image quality)
	Aperture value	f/2.8 (Appropriate depth of field)
	Image format	Original format (retaining complete information)
Multispectral parameters	Blue light band	450nm±20nm
	Green light band	560nm±20nm
	Red light band	650nm±20nm
	Red border band	730nm±20nm
	Near-infrared band	840nm±40nm
Data management	Acquisition frequency	Once every 15 days, for a total of 8 times
	Storage method	Local solid-state drive + cloud backup
	Data volume	Each time it's approximately 50GB, totaling 400GB

3.2 Maize Image Processing

Due to the influence of atmospheric attenuation effect, systematic error, terrain undulation and atmospheric turbulence in the process of flight acquisition, it brings great difficulties to the analysis and interpretation in the later stage, and directly affects the effect of judging the crop growth status. This paper proposes a series of preprocessing methods based on radiometric calibration, image alignment, image filtering and image sharpening to remove the influence of other confounding factors.

Radiometric calibration link to solve the distortion caused by inconsistent sensor response, atmospheric effects and changes in lighting conditions on the image radiation characteristics, using absolute radiometric calibration method based on the standard reflective plate, through the standard grayscale plate imaging to establish a linear relationship between the digital quantization value and the true reflectance, the calibration formula is:

$$\rho_\lambda = \frac{DN_\lambda - DN_{dark}}{DN_{ref} - DN_{dark}} \times \rho_{ref} \tag{7}$$

where ρ_λ is the corrected surface reflectivity, DN_λ is the numerical quantized value of the target image element, DN_{dark} is the value of the dark current, DN_{ref} is the numerical quantized value of the standard reflector plate, and ρ_{ref} is the known reflectivity of the standard reflector plate.

Atmospheric correction is accurately calculated using the 6S radiative transfer model, which integrates Rayleigh scattering, Mie scattering, gas absorption and other atmospheric effects, and calculates the atmospheric transmittance rate and path radiance value by inputting the solar zenith angle, azimuth angle, atmospheric visibility and other parameters at the moment of flight to realize the accurate conversion from apparent reflectance to true reflectance on the surface.

Geometric correction technology eliminates the geometric deformation caused by lens distortion, platform attitude change, terrain undulation, etc. The polynomial geometric correction model based on ground control points is adopted, and 20 high-precision ground control points are uniformly distributed in the test area, and real-time dynamic carrier phase differencing technology is utilized to obtain centimeter-level positioning accuracy coordinate information, and to establish the transformation relationship between the image coordinate system and the geographic coordinate system. The geometric transformation model is in the form of a quadratic polynomial:

$$\begin{cases} X = a_0 + a_1 x + a_2 y + a_3 xy + a_4 x^2 + a_5 y^2 \\ Y = b_0 + b_1 x + b_2 y + b_3 xy + b_4 x^2 + b_5 y^2 \end{cases} \tag{8}$$

where (x, y) is the image coordinates, (X, Y) is the geographic coordinates, and a_i and b_i are the transformation parameters, which are solved by the least squares method and the pixel resampling is performed by bilinear interpolation method, and the geometrical correction accuracy is controlled to be less than 0.5 image elements.

In order to reduce the impact of multiple noise sources such as thermal noise, quantization noise and transmission process noise generated by the sensor, the image denoising uses the adaptive Wiener filtering algorithm; which adjusts the filter coefficients according to the local statistical characteristics of the image to take into account the denoising effect and the protection of the details, and the frequency-domain expression of the filter is:

$$H(u,v) = \frac{|H_0(u,v)|^2}{|H_0(u,v)|^2 + \dfrac{S_n(u,v)}{S_f(u,v)}} \tag{9}$$

where $H_0(u,v)$ is the ideal system transfer function, $S_n(u,v)$ is the noise power spectral density, and $S_f(u,v)$ is the signal power spectral density.

Image enhancement processing through the histogram equalization, contrast stretching, sharpening filtering and other technical means to improve the image visual effect and information expression ability, histogram equalization using the cumulative distribution function transform to achieve gray level redistribution, the transformation function is defined as:

$$s = T(r) = (L-1)\sum_{i=0}^{k} p_r(r_i) = (L-1)\sum_{i=0}^{k} \frac{n_i}{n} \tag{10}$$

where s is the output gray value, r is the input gray value, L is the total number of gray levels, $p_r(r_i)$ is the probability density of gray level r_i, n_i is the number of pixels of gray level r_i, and n is the total number of pixels in the image.

Contrast stretching extends the dynamic range of the image by a linear transformation, the transformation formula is:

$$g(x,y)=\frac{f(x,y)-f_{\min}}{f_{\max}-f_{\min}}\times 255 \tag{11}$$

where $f(x,y)$ is the original pixel value, $f_{\min}$ and $f_{\max}$ are the image minimum and maximum values respectively, and $g(x,y)$ is the transformed pixel value.

The sharpening filter uses Laplace operator to enhance the image edge and detail information, and the filter kernel is defined as:

$$\nabla^2 f=\frac{\partial^2 f}{\partial x^2}+\frac{\partial^2 f}{\partial y^2} \tag{12}$$

The quality assessment system establishes multi-dimensional evaluation indexes including signal-to-noise ratio, contrast ratio, sharpness, color fidelity, etc. The signal-to-noise ratio is calculated by the formula:

$$SNR=10\log_{10}\frac{\sigma_s^2}{\sigma_n^2} \tag{13}$$

where σ_s^2 is the signal variance and σ_n^2 is the noise variance.

3.3 Feature Extraction and Model Construction

3.3.1 Feature extraction

The biggest advantage of the deep learning model applied to corn growth evaluation is that the method can automatically extract the input data effectively, and by designing an end-to-end learning method, the remote sensing image is used as the input layer and the growth evaluation index is the output layer. CNN, with the characteristics of local sensing field, weights sharing and translation invariance, can effectively extract the geometrical, textural and spectral features of the corn crop on the remotely sensed image, and overcome the problem of poor adaptation of the traditional manual feature selection method to the field environment of crops. The CNN can effectively extract the geometric, texture and spectral features of the corn crop from remote sensing images, and overcome the problem of poor adaptability of the traditional manual feature selection method to the field environment of the crop.

In the feature extraction network designed in this paper, the multi-scale feature fusion strategy applies convolutional branches with different receptive field sizes to the same set of images in parallel to obtain the local and overall features of the corn plant. The small receptive field convolutional layer at the front end of the network is used to learn local features such as leaf texture and contour, and the large receptive field convolutional layer at the back end of the network is used to learn the shape and distribution of the whole plant.

The feature extraction process can be described as a composite function of multilayer nonlinear transformations, let the input multispectral remote sensing image be $X\in\mathbb{R}^{H\times W\times 5}$, H and W denote the height and width of the image, respectively, and 5 denotes the five spectral bands, and the output feature maps of the convolution operation in the l th layer are calculated by the formula:

$$F^{(l)}=\sigma\left(W^{(l)}*F^{(l-1)}+b^{(l)}\right) \tag{14}$$

where $W^{(l)}$ denotes the convolutional kernel weight tensor of the lth layer, * denotes the convolution operation, $b^{(l)}$ is the bias vector, $\sigma(\cdot)$ is the ReLU activation function, and $F^{(0)} = X$ is the input image.

In order to enhance the network's ability to perceive maize plant features at different scales, this paper introduces a multi-scale feature pyramid structure into the network, and realizes effective integration of information by fusing feature maps at different levels, and the feature fusion operation is defined as:

$$F_{fused} = \sum_{i=1}^{n} \alpha_i \cdot Upsample\left(F^{(i)}\right) \tag{15}$$

where α_i is the learnable fusion weight, $Upsample(\cdot)$ denotes the upsampling operation, and n is the number of feature layers involved in fusion.

3.3.2 Model Architecture Design

In the maize growth evaluation model proposed in this paper, considering the characteristics of the maize growth evaluation task and the practical application requirements, the number of network layers is set to 16, and at the same time, the batch normalization operation is added after each group of convolution operations to improve the model performance and convergence speed. The added attention mechanism allows the network to focus on the most important positions for the judgment of the growth, and filter out some irrelevant information through the spatial attention weights to obtain better characterization ability.

The model architecture parameters are configured as shown in Table 2, and the total number of parameters reaches 544836. Among them, the application of residual connection structure solves the problem of gradient vanishing in deep network training, enabling the network to learn more complex feature representations, and the model training adopts a staged strategy, using ImageNet pre-training weights for initialization. Then, fine-tuning is performed on the agricultural remote sensing dataset, and this migration learning method significantly improves the learning effect of the model under small sample conditions.

Table 2: Model architecture parameter configuration

Network layer type	Output size	Number of parameters	Function description
Input layer	224×224×5	0	Multispectral remote sensing image input
Convolutional layer 1	224×224×64	9664	Basic feature extraction
Pooling layer 1	112×112×64	0	Dimension reduction and feature selection
Convolutional layer 2	112×112×128	73856	Mid-level feature extraction
Pooling layer 2	56×56×128	0	Middle-level feature extraction
Convolutional layer 3	56×56×256	295168	Further Longwei
Attention layer	56×56×256	33025	High-level semantic feature extraction
Global pooling layer	1×1×256	0	Feature enhancement in key areas
Fully connected layer 1	512	131584	Feature mapping and nonlinear transformation
Output layer	3	1539	Output of growth assessment results
Total	-	544836	The total number of online references

In order to ensure the validity and stability of the conclusions, a variety of cross-validation methods are used in the process of evaluating and testing the model, and all the sample data are divided into three parts according to a certain ratio: the training set, the validation set, and the testing set, and the testing set is used to assess the degree of adaptation of the model in the unknown samples; at the same time, not only root-mean-square error, average absolute error are used in the evaluation process, Meanwhile, in the evaluation process, not only quantitative methods such as root mean square error, mean absolute error, and coefficient of determination are used, but also qualitative evaluation methods such as confusion matrix diagrams and checking accuracy and completeness diagrams are used.

3.3.3 Model training

In this paper, an end-to-end supervised learning approach is adopted to update the network weights during the model training process, i.e., iterative training of the model is carried out in a way that reduces the error between the predicted value and the actual value, and since the evaluation of maize growth status contains multiple aspects, the common effect of different penalty terms is added to the loss function in order to improve the prediction accuracy of evaluation indexes of different dimensions (e.g., plant height, LAI, biomass, etc.):

$$L_{total} = \lambda_1 L_{height} + \lambda_2 L_{LAI} + \lambda_3 L_{biomass} + \lambda_4 L_{reg} \tag{16}$$

where L_{height}, L_{LAI}, $L_{biomass}$ denote the mean squared error loss of plant height, leaf area index and biomass, respectively, L_{reg} is the regularization term, and λ_i is the weight coefficients of each loss.

During the training process, the Adam optimizer was used to update the parameters in the network, and the learning rate was set to 0.001, and the batch size was set to 32. 200 epochs were trained in total; in order to prevent the occurrence of overfitting phenomenon, an early stop mechanism was set. In addition, data enhancement is also very important to improve the performance of the model, so various enhancement methods of the image such as random rotation, flipping, scaling, and brightness change are utilized to increase the number of training sets, which to a certain extent compensates for the problem of sample scarcity and category imbalance in the remote sensing scenarios of agriculture.

The trained model can be used to monitor the growth of maize, and the predicted values of maize plant height, LAI and dry matter weight can be obtained after inputting the preprocessed UAV remote sensing images, and the compression and optimization operations are carried out during the deployment process, and the network pruning and quantization techniques are used to reduce the size of the model to less than one-tenth of the size. The model size was reduced to less than one-tenth by using network pruning and quantization techniques, which greatly improved the inference speed without affecting the prediction accuracy.

4 Results and analysis of maize growth assessment experiments

4.1 Evaluating experimental subjects

This experiment took X city as the central experimental area (39°28′-39°35′N, 115°44′-115°58′E), X city is located in the warm temperate semi-humid continental monsoon climate zone, with an average temperature of 11.5°C, a rainfall of 550 mm, a moist brown soil texture, a moderate organic matter content, and a soil pH of 7.2-7.8. The above factors are to ensure that the maize growth and development of the The above factors are the basic conditions to ensure the growth and development of maize. 60hm² of consecutive planting blocks in the 120hm² experimental area was selected as the experimental area, which had a high degree of flatness, a slope of no more than 2°, and a well-developed field road system, which was favorable for the synergistic implementation of unmanned aerial vehicle aerial surveys and manual surveys. Cultivation in the small area is carried out according to the same agricultural cultivation measures, using the local leading varieties, sowing specifications for the large row spacing of 60cm × small row spacing of 60cm × 25cm, planting density of 67,500 plants/hm², fertilizer application method for the basic fertilizer + fertilizer, the amount of basal application of compound fertilizer is 750kg/hm²; node application of 300kg/hm² urea, watering methods are adopted sprinkler irrigation, to take the The above series of measures were taken to ensure the homogeneity of water and fertilizer conditions in each sub-district.

4.2 Assessment results and analysis

4.2.1 Overall assessment results

The results of the model evaluation are shown in Table 3. The results comprehensively confirmed the excellent performance of the proposed method in the maize growth assessment task, and the plant height prediction task showed an obvious change pattern in stages. In the seedling stage, the prediction accuracy was relatively low at 89.3% due to the small plant size and strong soil disturbance in the background. With the gradual growth of corn plants and the increase of canopy coverage, the prediction accuracy at the nodulation stage increased to 92.7%. The peaks of 94.8% and 95.2% were reached at the trumpet stage and staminate stage, respectively, and the morphology of maize plants was most recognizable at this stage, while the prediction accuracy was slightly reduced at the filling stage and maturity stage due to the yellowing of leaf aging; the estimated R² of leaf area index (LAI) was at a high level throughout the whole growing season (0.79-0.91), with the highest level of 0.91 at the trumpet stage, where maize had the highest number of leaves, and the highest activity of the leaves. At the same time, the leaf activity was the highest, and the multispectral image could better reflect the canopy structure characteristics. The relative errors of biomass estimation ranged from 8.3% to 15.8%, with the highest accuracy (8.3%) at the stamen pumping stage, which was much lower than that of the traditional remote sensing method (20%-30%), and the correlation between the normalized vegetation index (NVI) and the ground-based measurements varied with the reproductive stage in a way that was basically consistent with that of the leaf area index (LAI), with the best correlation (0.92) at the big trumpet stage, which indicated that multispectral remote sensing has a strong vegetation monitoring ability.

Table 3: Model Evaluation Results

Evaluation index	Seedling stage	Jointing stage	Trumpet stage	Tasseling stage	Grouting stage	Mature stage
Plant height prediction accuracy (%)	89.3	92.7	94.8	95.2	93.6	91.4
Leaf area index R^2	0.82	0.87	0.91	0.89	0.85	0.79
Biomass estimation error (%)	15.8	12.4	9.7	8.3	10.6	13.2
NDVI correlation coefficient	0.78	0.84	0.92	0.88	0.81	0.73
Handling time (seconds/image)	0.067	0.071	0.069	0.068	0.072	0.070
Model confidence level (%)	87.2	91.5	95.3	94.7	90.8	86.9

4.2.2 Effect of different variables on maize growth assessment

Maize fertility stage changes directly affect the assessment accuracy of UAV remote sensing image processing methods based on artificial intelligence algorithms, which is because the evolutionary law of canopy structure features determines the quality of remote sensing signals. Analysis of the impact of different variables on the results of maize growth assessment Table 4 shows that the fertility stage has a very large impact on the growth assessment of maize due to the dynamic changes in its canopy structure ($r=0.89$, $p<0.001$). In addition, the results of maize growth assessment were also affected by light conditions, mainly because light conditions lead to differences in the quality of spectral response, and the correlation coefficient between the two reached 0.76. In addition to this, atmospheric transparency, soil background, wind speed effects and plant density all had some significant effects on the assessment results. In contrast, the effects of varietal differences ($r=0.43$, $p>0.05$) and flight altitude pairs ($r=-0.38$, $p>0.05$) on the assessment results were not significant.

Table 4: The Impact of Different Variables on the Evaluation Results of Corn Growth

Influencing variable	Degree of influence	Correlation coefficient	Significance level
Reproductive stage	Extremely significant	0.89	$p < 0.001$
Lighting conditions	Significant	0.76	$p < 0.01$
Atmospheric transparency	Significant	0.72	$p < 0.01$
Soil background	Medium significant	0.58	$p < 0.05$
Wind speed influence	Medium significant	-0.54	$p < 0.05$
Plant density	Medium significant	0.61	$p < 0.05$
Variety differences	Not significant	0.43	$p>0.05$
Flight altitude	Not significant	-0.38	$p>0.05$

The effects of different maize fertility stages on the assessment results were further analyzed, and the results are shown in Figure 1. It was found that the big trumpet stage and the male pulling stage represent the peak stage of maize nutrient growth, when the number of leaves reaches the maximum value, and the chlorophyll content is at the highest level, and the canopy structure presents the best spectral response characteristics, and the assessment model shows the optimal feature extraction ability in these two periods, and the accuracy of the estimation of the leaf area index reached 94.2% and 93.0%, and the accuracy of the assessment of the biomass reached 93.5% and 94.6%, and the plant height prediction accuracy also achieved good results.

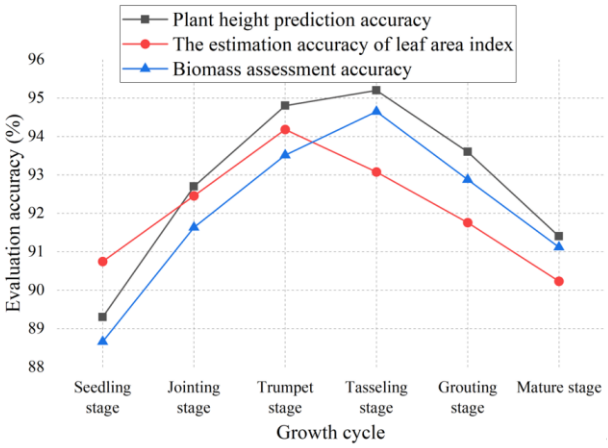

Figure 1: Analysis of the changing trends of algorithm performance at Different Growth stages

From the above analysis, it can be seen that remote sensing image processing based on AI algorithms has outstanding technical advantages such as automatic feature learning, multi-scale information fusion, and end-to-end processing, etc. The deep CNN model utilizes multiple nonlinear mappings to automatically mine and extract high-level semantic features that are highly correlated with the maize growth, which are usually difficult to be characterized by manually designed features, and then higher prediction result accuracy can be obtained. The multi-scale feature fusion makes it possible for the algorithm to extract both the detailed features of a single corn plant and its overall contour shape features, thus forming more representative features for describing the plant's growth. In addition, the use of end-to-end processing process can overcome the effect of cumulative errors caused by the previous multi-step processing of feature extraction, feature selection, classifier construction, etc., making the system more robust.

5 Conclusion

In this paper, we propose an intelligent estimation method of corn growth for UAV images, which has obvious advantages over other estimation methods; automatic feature learning of images using CNN, avoiding the process of manually designing feature vectors, and realizing high-precision estimation results, with an average height estimation accuracy of more than 95.2%, a coefficient of determination of the leaf area index R^2 of more than 0.91, and a biomass estimation error of less than 8.3%. In addition, feature learning on images of different sizes and weighted summation of features at different levels ensure the attention to the region of interest and the effective combination of local features and overall features. Looking forward to the future research direction, we will carry out research on data fusion methods based on various heterogeneous data such as hyperspectral, LiDAR, meteorological and soil data; Strengthen the interpretability analysis of the modeling process, improve the visualization of the model to obtain higher confidence; use more orders of magnitude of data information and transfer learning strategies to achieve effective prediction of the growth status of different regions and crops; explore the combination of deep neural networks and edge intelligence and apply them to agricultural production. Promote the application and promotion of lightweight model design optimization methods to achieve digital and intelligent upgrading of precision agriculture under resource constraints.

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