UAV-BASED AUTOMATIC ASSESSMENT OF FLAX FIBER PRODUCTION POTENTIAL USING STEM LENGTH ESTIMATION AND MACHINE LEARNING

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Abstract. Flax (*Linum usitatissimum*) is an important crop for fiber and oil production, and stem length is one of the key indicators determining fiber yield and raw material quality. However, field-based assessment of flax stem length and quality traits remains labor-intensive and time-consuming. This study presents a high-throughput quality parameter assessment approach using unmanned aerial vehicle (UAV) imagery and machine learning based on deep neural networks to predict the flax stem length. High-resolution RGB aerial images of flax field plots were collected together with ground-truth measurements of average stem length. A deep convolutional neural network (ResNet-50) pre-trained on ImageNet was used to extract visual features from the images, which were subsequently aggregated and employed in a CatBoost regression model for the stem length estimation. Extensive preprocessing, including image rotation-based augmentation, patch tiling, and filtering, was applied to ensure robust feature extraction. The proposed model achieved a coefficient of determination (R^2) of 0.76 on an independent test set, with a mean absolute error of 4.3 cm and a root mean square error of 5.8 cm. These results indicate that approximately 76% of the variability in the flax stem length is explained by image-derived features, while prediction accuracy remains within practical limits for field applications. Notably, the visual features extracted by the neural network demonstrated higher predictive significance than metadata such as the flax variety or lighting conditions. The study demonstrates that UAV-based imaging combined with deep feature extraction and gradient boosting enables practical and scalable field-level quality assessment in flax production, supporting rapid evaluation of crop stature and indirect estimation of fiber yield potential over large agricultural areas.

Keywords: unmanned aerial vehicle (UAV), flax stem length, ouality assessment, machine learning, neural networks, fiber production.

Introduction

Global flax cultivation has been increasing due to the growing demand for flax fiber and seeds [1]. Flax is a crop of complex utilization that provides products for both food and industrial applications [2]. The main outputs of flax cultivation are seeds and fiber; however, the remaining stem biomass is also processed, for example into biomass rolls and related materials [3]. The structural and physical properties of flax stems, as well as the harvesting method applied, considerably influence harvesting and the quality of the collected stems [4]. Longer stems generally provide higher fiber yield and improved fiber quality, making the stem length an important indicator for evaluating the flax production potential and the suitability of raw material for fiber processing [2]. This is particularly important for fiber-oriented flax production, [4], biomass processing quality [2], quality of formed biomass rolls [3], and technological parameters [5]. Consequently, accurate and timely assessment of the stem length under field conditions is essential for quality monitoring and optimization of harvesting and processing strategies.

Traditional evaluation of flax stem length relies on manual field sampling and ground-based measurements. Although accurate, these methods are labor-intensive, time-consuming, and impractical for frequent monitoring or large cultivation areas. These limitations slow down decision-making and make it harder to scale quality assessment in flax production.

Recent technological advances have enabled the integration of remote sensing, automation, and data-driven analysis for structural assessment. Unmanned aerial vehicles (UAVs) equipped with imaging sensors enable rapid, non-destructive surveying of agricultural fields [6]. High-resolution UAV imagery captures detailed visual information over large areas within short time frames, providing an effective basis for automated field-level assessment [7]. UAV-based monitoring has been successfully applied for quantitative estimation of crop structural and yield-related parameters in several agricultural species. Deep learning analysis of UAV data has been successfully applied to yield prediction in cotton [8] and rice [9], and to yield estimation in wheat based on canopy structural features [10]. These studies demonstrate that UAV imagery combined with machine learning can capture canopy characteristics correlated with plant height, biomass, and productivity traits. In the context of flax, the application of UAV-based imaging has been scarcely studied. However, UAV imagery can be used to assess flax stem quality through color characteristics related to stem parameters [7].

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UAV remote sensing combined with machine learning has enabled automated estimation of structural crop traits. UAV imagery combined with elevation data has been used to estimate wheat plant height and biomass [11]. Three-dimensional UAV photogrammetry has enabled precise estimation of crop height and above-ground biomass [12]. Deep learning applied to UAV imagery has also been used to evaluate plant density [13]. Hyperspectral UAV analysis has enabled estimation of leaf area index [14]. Deep learning has further been applied to predict crop maturity traits from UAV imagery [15]. Additional sensing modalities such as LiDAR combined with deep learning enabled accurate prediction of plant height and crown structure [16].

Further development of UAV-based phenotyping for flax demonstrated the feasibility of predicting fiber and seed yield using automated image analysis [17]. Altogether, these studies demonstrate that image-derived features extracted from UAV data can serve as reliable predictors of crop structural traits. However, direct assessment of flax stem length from RGB UAV imagery at the field-plot level remains insufficiently investigated.

Materials and methods

This study was conducted on experimental flax fields (plots) where UAV imagery and ground-based measurements were collected. For each plot corresponding to a single UAV image, reference measurements of average stem length were performed from plant samples and used as ground truth data. Additional metadata included flax variety, plant age, planting density, UAV flight altitude, and lighting conditions during image acquisition. In total, 52 plot-level observations with paired UAV imagery and stem length measurements were included in the dataset. Table 1 presents the metadata used in the study. These variables were included as additional predictors in the regression model to account for differences in the plant development stage and image acquisition conditions. The measured average stem length was used separately as the target variable (ground truth) for regression modelling.

Table 1

Metadata used in the study (sample of dataset)

Plot	Variety	Sowing date	UAV date	Growth stage	Plant age, days	UAV altitude, m
1	Miandr	03.05.2025	06.06.2025	Stem elongation	34	25
2	Miandr	03.05.2025	28.06.2025	Flowering beginning	56	30
3	Miandr	03.05.2025	15.07.2025	Early ripening	73	25
4	Miandr	03.05.2025	12.08.2025	Ripening	101	40
5	Lirina	01.05.2025	06.06.2025	Stem elongation	36	25
6	Lirina	01.05.2025	28.06.2025	Flowering	58	30
7	Lirina	01.05.2025	15.07.2025	Early ripening	75	25
8	Lirina	01.05.2025	12.08.2025	Ripening	103	40
9	Lirina	14.05.2025	06.06.2025	Vegetative	23	25
10	Lirina	14.05.2025	28.06.2025	Bud stage	45	30
11	Lirina	14.05.2025	15.07.2025	Early ripening	62	25
12	Lirina	14.05.2025	12.08.2025	Ripening	90	40

UAV surveys were conducted on 6 June, 28 June, 15 July, and 12 August to capture canopy changes from stem elongation to the ripening stage. Plant age ranged from 23 to 103 days, ensuring sufficient variability in the stem length and canopy structure for model training. All UAV surveys were conducted under stable illumination conditions. Image acquisition was performed during daytime within a similar time window (approximately between 11:00 and 14:00) to ensure a consistent sun angle and minimize the effect of shadows on canopy images. Most flights were carried out under clear or slightly cloudy weather conditions, providing uniform natural illumination. This ensured that color characteristics of the canopy were comparable across different survey dates and reduced variability in image brightness caused by changing illumination conditions.

A foldable quadcopter UAV (FIMI X8 SE, Xiaomi, China) equipped with an integrated RGB camera (12 MP CMOS sensor, 26 mm equivalent focal length) was used for aerial imaging (Fig. 1). The imaging system captured only visible spectral bands; no multispectral or near-infrared sensors were used. The UAV flew at an altitude of 20-40 m above the ground level (AGL), covering each field with approximately 80% forward and 70-80% side overlap to ensure complete plot coverage and reliable orthomosaic reconstruction. Flights were scheduled at critical growth stages (e.g. bud formation, flowering, beginning of ripening) when differences in the plant condition are most pronounced. The ground image resolution was approximately 3-5 cm·pixel^{-1} depending on the flight altitude and camera geometry. Each image was geo-tagged using the UAV's onboard GNSS positioning system.

Images were acquired under stable illumination conditions with a nadir-oriented camera to obtain orthogonal views of the crop canopy. Images were subsequently segmented as shown schematically in Fig. 1 a.. Plot boundaries were delineated according to the experimental field layout, and individual plot images were extracted to ensure one-to-one correspondence between UAV observations and ground stem-length measurements.

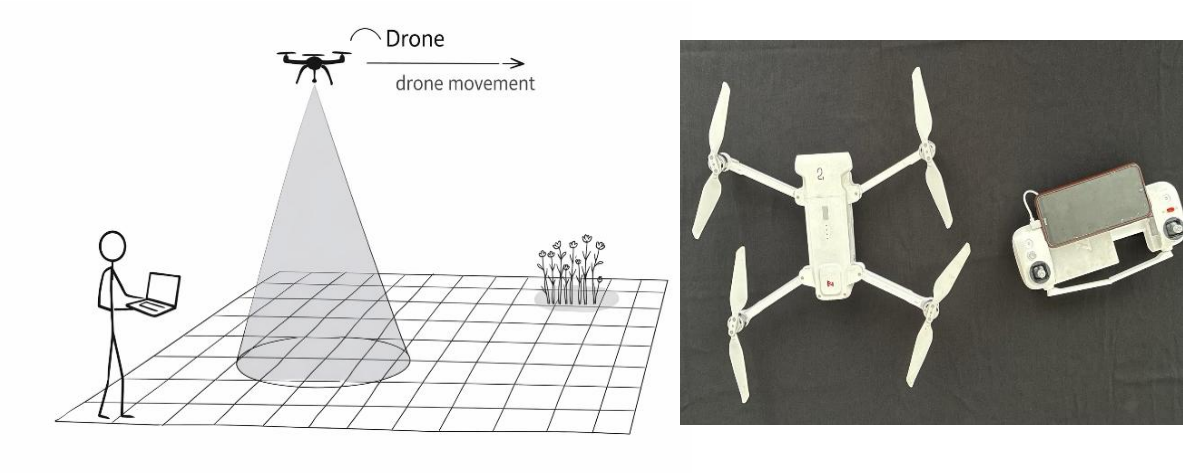

Fig. 1. **UAV-based flax field imaging system:** a – schematic layout of UAV survey geometry and plot coverage; b – foldable quadcopter UAV (FIMI X8 SE, Xiaomi) with integrated RGB camera

Due to the limited number of original images, data augmentation and tiling were applied to improve the model robustness. Each UAV image was augmented by rotation at multiple angles and divided into overlapping 256×256 pixel patches. Tiles containing non-informative areas were removed based on a predefined threshold. This procedure increased the effective number of training samples and reduced sensitivity to canopy orientation while preserving plot-specific visual patterns.

Deep visual features were extracted from image patches using a convolutional neural network (CNN), specifically the ResNet-50 architecture pre-trained on ImageNet. The final classification layer was removed, and the activations of the penultimate layer were used as feature vectors. This transfer-learning approach enabled extraction of invariant descriptors of canopy texture and spatial structure from RGB imagery without training a deep model on a limited agricultural dataset.

For each plot image, patch-level feature vectors were aggregated into a single representation by computing statistical descriptors, including the mean, standard deviation, minimum, and maximum across all patches. The resulting fixed-length vector summarized the distribution of visual canopy features within each plot. Such aggregation preserved spatial variability information while producing a stable plot-level descriptor suitable for regression modelling (Fig. 2).

Stem length assessment was performed using a CatBoost regression model trained on the aggregated feature vectors. The dataset was randomly divided into training and test subsets using an 80/20 split. Model training incorporated regularization and early stopping to prevent overfitting. Feature importance analysis was applied to evaluate the contribution of image-derived features relative to auxiliary metadata.

Model performance was estimated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). All performance metrics were calculated on the independent test subset to assess predictive accuracy and generalization.

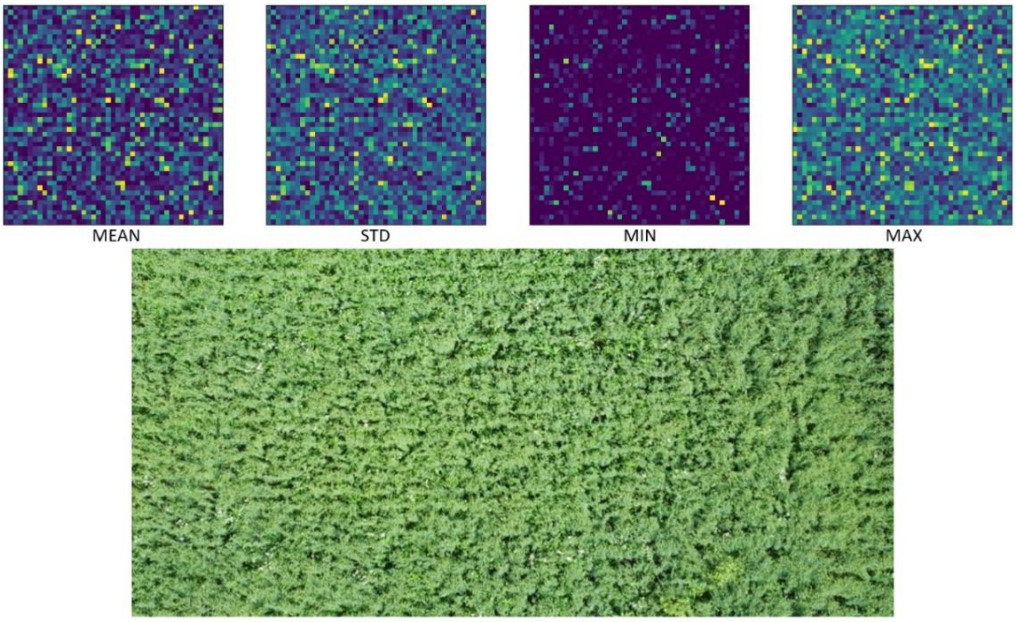

Fig. 2. **Plot-level distribution of aggregated CNN feature statistics (mean, standard deviation, minimum, maximum) derived from patch-based RGB analysis**

Results and discussion

The CatBoost regression model demonstrated reliable predictive performance in assessing flax stem length from UAV imagery. On the independent test dataset, which was not used during model training, the model achieved a coefficient of determination (R^2) of 0.76, indicating that approximately 76% of the variability in average stem length across different plots was explained by image-derived features. The mean absolute error (MAE) on the test set was 4.3 cm, while the root mean square error (RMSE) reached 5.8 cm. Given that the observed stem lengths in the dataset ranged from approximately 50 to 90 cm, the obtained error magnitude corresponds to less than 10% of the measurement range. The relatively small difference between MAE and RMSE indicates stable predictive performance without extreme outliers. Table 2 summarizes the quantitative performance metrics of the proposed model on unseen data. These results indicate that UAV-derived RGB information contains sufficient structural variability to estimate plot-level differences in the flax stem length.

Table 2

Performance metrics of the flax stem length assessment model on the test dataset

Metric	Value	Unit
R^2 (Coefficient of Determination)	0.76	–
MAE (Mean Absolute Error)	4.3	cm
RMSE (Root Mean Square Error)	5.8	cm

From a practical perspective, this accuracy enables reliable differentiation between plots with moderate and high stem length values. For example, for plots with measured stem lengths around 80 cm, predicted values typically remain within a deviation of approximately 6 cm, which is sufficient for comparative field-level assessment of crop stature in fiber-oriented flax production.

To assess the distinct contributions of different input data sources, the performance of the full model was compared against two baseline configurations: one trained exclusively on non-visual metadata and another using only image-derived CNN features. The metadata-only model showed limited predictive capability ($R^2 < 0.2$), indicating that basic agronomic descriptors alone do not adequately capture spatial variability in the stem length.

The model trained solely on CNN features demonstrated significant predictive capability, achieving R^2 of 0.63. This result proves that visual information from the canopy is a strong and independent predictor of the stem length. However, the highest accuracy was achieved by the full model, which combined both CNN features and metadata, reaching R^2 of 0.76. The observed improvement suggests that the developmental stage information complements structural canopy descriptors extracted from aerial imagery. The importance of CNN-derived features in the full model is illustrated in Fig. 3.

This demonstrates a synergistic effect between the two data sources. While the visual features provide a robust, data-driven assessment of the crop actual condition, the metadata (particularly plant age) serves as a powerful contextual baseline. The model effectively learns to use the visual features to correct and refine the general trend provided by the metadata, leading to a more accurate and reliable final prediction.

An ablation study was conducted to investigate the role of color information in stem length assessment. In this experiment, UAV images were converted to grayscale and enhanced using Contrast Limited Adaptive Histogram Equalization, thereby preserving texture and structural information while removing color cues. The grayscale-based model exhibited a moderate reduction in predictive performance compared to the RGB-based model, confirming that color information contributes to stem length assessment, potentially reflecting differences in plant maturity or physiological condition. Nevertheless, the grayscale model retained reasonable accuracy, indicating that the canopy texture, density, and structural patterns alone possess substantial predictive power. This indicates that both spectral (color) and spatial canopy characteristics contribute to the stem length estimation from UAV imagery.

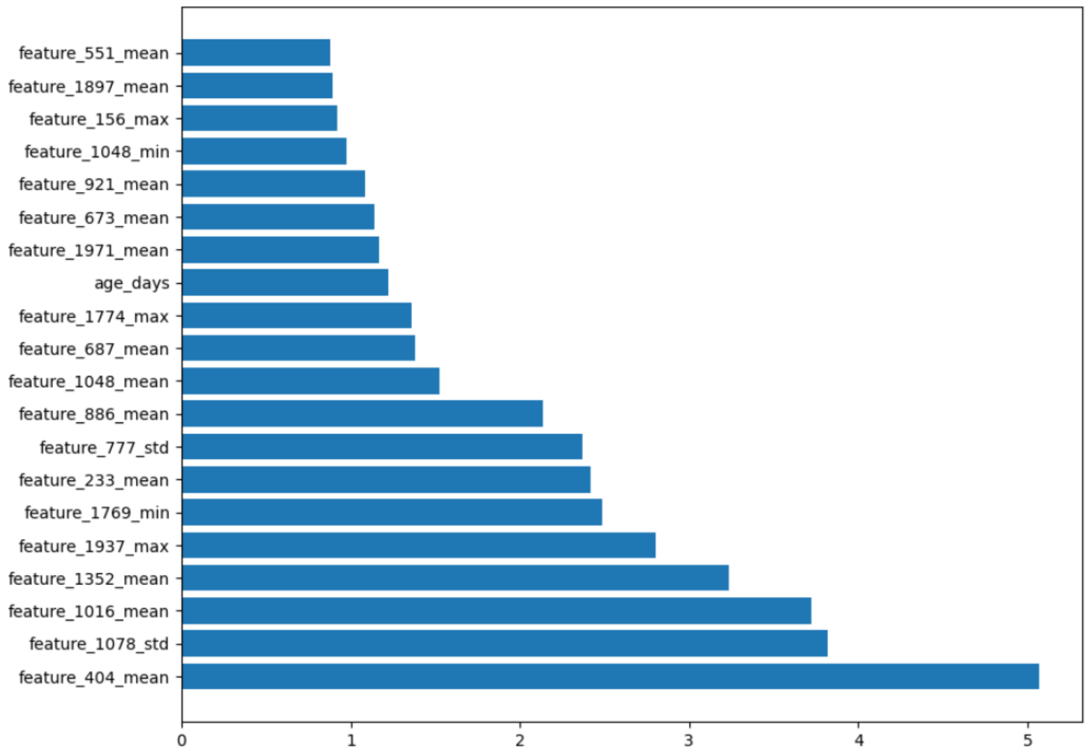

Fig. 3. **Relative importance of the 20 most influential CNN-derived feature components in the CatBoost regression model for flax stem length estimation**

Table 3 presents the comparative performance of the evaluated model configurations. The CNN-only model achieved $R^2 = 0.63$ and MAE = 9.5 cm, whereas integration of metadata increased R^2 to 0.76 and reduced the prediction error to MAE = 4.3 cm. The metadata-only model showed low predictive capacity ($R^2 = 0.18$), confirming that UAV-derived canopy descriptors are the primary source of stem-length information.

Table 3

Comparison of model configurations for flax stem length assessment

Model configuration	R^2	MAE, cm
Metadata only	< 0.20	> 10
CNN features only	≈ 0.63	≈ 9.5
CNN features + metadata	≈ 0.76	≈ 4.3

A qualitative analysis of the model predictions further supported the quantitative results. Visualization of the predicted versus measured stem length values showed a strong clustering of data points around the 1:1 reference line, confirming good agreement between predictions and ground measurements. Minor underestimation was observed for a small number of plots with the highest stem length values, which may be attributed to the limited representation of extreme cases in the training dataset. Overall, prediction errors were randomly distributed across the stem length range, and no systematic bias was detected, indicating that the model captures meaningful relationships between the UAV-derived visual features and flax stem length across the observed range of crop development conditions.

Conclusions

This study demonstrates the possibility of using UAV-based RGB imaging combined with deep feature extraction and machine-learning regression for automated assessment of the flax stem length as a quantitative quality indicator in field conditions. A processing pipeline combining high-resolution UAV RGB imagery, deep CNN feature extraction using a pre-trained ResNet-50 network, and CatBoost gradient boosting regression was developed and evaluated. The proposed approach achieved plot-level prediction accuracy, with a coefficient of determination of approximately 0.76, confirming its capability to reliably estimate the average stem length at the plot level. Through data augmentation, image tiling, and statistical feature aggregation, complex visual information from the flax canopy was transformed into informative predictors of the stem length, enabling non-destructive and scalable field assessment.

A key finding of this work is that the image-derived deep features extracted from RGB UAV imagery provide substantially higher predictive power than traditional non-visual metadata. The model captured differences related to the plant development and field conditions through the canopy structure and visual characteristics. The use of transfer learning proved effective for feature extraction under limited dataset conditions, allowing robust generalization while reducing data requirements. The combination of deep feature extraction and gradient boosting regression thus represents a practical image-analysis approach for the stem-length estimation in flax.

From an applied perspective, the proposed method offers a valuable tool for field-level quality monitoring in flax fiber production. UAV-based assessment enables rapid surveying of large cultivation areas and provides timely information on stem length distribution without labor-intensive manual measurements. Such capability can support decision-making in production systems, including identification of spatial variability within fields, monitoring of crop development, and evaluation of crop uniformity relevant to fiber quality. The presented framework is not limited to flax and may be adapted to other crops or structural quality parameters by retraining the model with appropriate imagery.

Overall, the study highlights the potential of integrating UAV remote sensing and machine learning for modern, data-driven quality assessment in agricultural production systems. Future research may extend the approach to additional flax quality indicators, incorporate multispectral or LiDAR data, or exploit time-series UAV imagery to analyze growth dynamics. As UAV platforms and artificial intelligence methods continue to evolve, such image-based assessment tools are expected to play an increasingly important role in precision agriculture and fiber crop production.

Author contributions

Conceptualization, O.Y.; methodology, O.P.; software, O.P.; validation, O.Y.; formal analysis, O.Y.; investigation, O.Y.; data curation, O.P. and O.Y.; original draft preparation, O.Y.; writing – review and editing, O.P.; visualization, O.P. and O.Y.; project administration, O.P. All authors have read and agreed to the published version of the manuscript.

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