



Deep Learning-based RGB Image Modelling for Multi-component Pasture Biomass Estimation in Precision Grazing

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ABSTRACT

Background: Accurate estimation of pasture biomass is significant for managing grazing, feed distribution and overall livestock productivity sustainably. The classical methods of cutting and weighing are the most trustworthy worst-case scenario but they are also foul slow, demanding much labour and are not useful for very large areas.

Methods: This research intended to construct a minimalist deep-learning framework that can accurately estimate various pasture biomass components from inexpensive RGB images and corresponding field data. The material used for the experiment included 1,785 tree-top images taken from Australian pastures, all linked to ground measurements of biomass fractions, vegetation indices and plant-height data. The proposed architecture brings together depth wise-separable convolutions, channel-attention mechanisms and Fourier feature projections to sink the spatial detail and capture the vegetation patterns. A stratified train-validation split and controlled augmentations were used to avoid data leakage and to boost the model's robustness.

Result: The validation obtained very consistent accuracy across the five fractions of biomass with a weighted determination coefficient of 0.81. The developed framework is a sustainable, non-invasive method for estimating pasture biomass and thus it gives huge advantages in precision grazing and sustainable livestock management.

Key words: Deep learning, Multi-output regression, Pasture biomass estimation, Precision grazing, RGB imagery, Sustainable livestock management.

INTRODUCTION

The global adoption of data-driven farming solutions has increased demand for improved biomass estimations. Traditional ground methods remain inefficient due to resource requirements. Deep learning, computer vision and RS provide scalable crop analysis capabilities (Akiva *et al.*, 2022; Barriguinha *et al.*, 2022; Maji *et al.*, 2022). Deep learning models like CNN, CNN-GRU effectively model spectral and environmental factors (Wang *et al.*, 2025; Lu *et al.*, 2024). Analysis of multispectral images enables biomass estimation and yield prediction (Menon *et al.*, 2025; Akcapınar and Apaydin, 2025). Remote Sensing provides non-destructive data, while vegetation indices integrated with deep learning deliver accurate results (Tian *et al.*, 2020; Menon *et al.*, 2025). AI-vision models enable precise biomass estimation (Padhiary *et al.*, 2024). This integration is revolutionizing the domain by improving precision (Kamangir *et al.*, 2024; Wang *et al.*, 2025).

Still, the issue of biomass forecasting endures among different plants and climate types because of differences in model generalization. Accordingly, the author scrutinizes: (1) What are the ways to achieve the maximum performance from the lightest DL architectures for biomass prediction? (2) Do the frequency-enhanced mechanisms play a role in improving the stability of the models? (3) What are ways in which DL-RS systems can contribute to sustainable crop management? AgroVisionNet is a combination of depthwise-separable residual blocks and Fourier features for the purpose of dealing with spectral-spatial dependencies. The model has shown better performance

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by giving lower R² error as compared to ResNet and CNN-GRU models when using CSIRO data. The study presents a fast biomass estimation model that is also effective in estimating crop biomass.

According to recent research, deep learning has proven to be very effective in agricultural imaging. VGG19 models have been used for the detection of plant diseases (Kashyap and Kashyap, 2025), while a combination of ResNet CNN and SVM has improved classification (Vidhya *et al.*, 2025). The use of attention-enhanced architectures helps in the detection of diseases (Ashwini and Uma, 2025)

and, at the same time, CNNs are able to detect wilting in soybeans (Na and Na, 2024). All these developments support the use of small models in agriculture. With the help of AI and ML, there has been a significant increase in the production of crops and agricultural GHG emissions have been reduced by 20% (Naeem *et al.*, 2025; Avasthi *et al.*, 2025). The obstacles encountered are mainly high expenses, the security of data and unavailability of properly trained staff. Among others, ML algorithms have greatly increased the accuracy of biomass estimation and predictive through multispectral data analysis (Menon *et al.*, 2025; Akcapinar and Apaydin, 2025). The use of AI in aquaponic systems has been suggested for nutrient regulation purposes (Chandramenon *et al.*, 2024). By using ML and DL models, forecasting of crop yields has become far more accurate than with traditional methods, while regression still applies for small-scale scenarios. The use of more sophisticated algorithms allows the prediction of the yields of wheat, maize and soybean by depending on the data from distant sensors and weather information (Johansen *et al.* 2020; Javed and Masrah 2024; Saleem *et al.* 2023). The combination of AI and IoT sensors for resource management in agriculture leads to sustainable practices (Pawde and Dave 2025; Avasthi *et al.*, 2025). The use of predictive analytics contributes to the improvement of the supply chain in terms of efficiency (Pallathadka *et al.*, 2023). Key challenges include: the need for expensive, high-quality and accurately labeled pictures to train Deep Learning systems (Johansen *et al.*, 2020; Abudu *et al.*, 2025), limited model generalization over different environments (Zheng *et al.*, 2025; Thammolest *et al.*, 2025) and the opacity of black box models (Cheng *et al.*, 2025; Wang and Yao, 2023). The lack of sufficient computing power also affects the use of Deep Learning in under-developed areas (Sangjan *et al.*, 2023). Data access, model interpretability and infrastructure costs are the three major areas that future research should focus on to ensure that the implementation is sustainable (Zheng *et al.*, 2025; Abudu *et al.*, 2025; Moussaid *et al.*, 2025).

The focus of this research work is on making the approach accurate, efficient and reproducible. The approach relies on RGB images and metadata. This approach doesn't need expensive sensors. The approach relies on minimal processing with a lightweight architecture.

MATERIALS AND METHODS

Dataset description

The experimental implementation and analysis were carried out at the Rajarambapu Institute of Technology, Department of Computer Science and Engineering, Rajaramnagar, Sangli, Maharashtra, during the 2025-2026 academic session. The dataset used in the present study was sourced from the CSIRO Biomass Prediction Challenge hosted on Kaggle (Liao *et al.*, 2025), consisting

of 1,785 field samples, where every sample was connected to an RGB image and the ground-measured biomass weights for the five components: Dry_Green_g, Dry_Dead_g, Dry_Clover_g, GDM_g and Dry_Total_g. Along with each sample, metadata are provided, which include image file path, NDVI values, average plant height, date of sampling and location information. Each .jpg file contains an image, which is assigned a common prefix identifier to connect it to a set of structured CSV files containing biomass data. An initial analysis of the data is conducted to examine data completeness, identify missing values, explore data for inconsistencies in values, as well as investigate data distribution for biomass values to ensure data readiness for regression modelling.

Data pre-processing

The entire pre-processing process aimed at obtaining clean input data and at eliminating the information sharing issue between the training and the validation samples. To make regression prediction less volatile, first, the extreme biomass records that went beyond the 99th percentile (111.76 g) were discovered and subsequently eliminated since these outliers greatly affected the updates of the gradients and thus the convergence of the model was skewed. The metadata table and the RGB image directory were then joined based on the common prefix that was extracted from each *sample_id*, thus generating a data frame containing image paths, biomass values, NDVI measurements and plant-height data. This integration ensured that each training instance had both the visual and the tabular features needed for multimodal learning.

To deal with group leakage-where several records from the same physical plot could be included in both the training and the validation sets-the dataset was split with a prefix-based stratified split, making sure that all the biomass parts of one sample prefix were allotted only to either the training or validation subset. The tabular features NDVI and height were then normalised using min-max scaling according to Eq. (1) to preserve the comparable numerical ranges:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad \dots(1)$$

All normalization parameters related to NDVI and plant height were calculated only on the training subset and afterward, the same parameters were applied to the validation data without any changes, thus preventing the possibility of unintentional information leakage.

In the image processing pipeline, all the RGB pictures were downsized to (400 × 200) pixels, converted to PyTorch tensors and then normalised for each channel with ImageNet statistics as per Eq. (2):

$$I_{\text{norm}} = \frac{1 - \mu}{\sigma} \quad \dots(2)$$

Through this process, compatibility with the convolutional backbone was guaranteed and stable training

was made possible. In addition to this, the training set underwent a mild augmentation that included random horizontal flipping and photometric jitter, which served to introduce the variability in illumination and canopy orientation in a controlled manner thus overfitting was diminished. The *PyTorch torchvision.transforms* library was used to carry out all the pre-processing steps and the eventual processed dataset was wrapped inside a custom Biomass Dataset loader to facilitate efficient training in batches.

Data augmentation

In order to make the model more robust against the natural variability of the pasture images, the controlled augmentation of data was applied to the training set. The photometric transformations were the means to eliminate the differences in light, shadow patterns and sensor exposures. The random brightness and contrast adjustments were applied by changing each pixel intensity (I) according to the Eq. (3):

$$I' = \alpha I + \beta \quad \dots(3)$$

Where,

(α) and (β)= The contrast and brightness factors respectively and they are randomly sampled within their predefined ranges.

By this operation, the model is exposed to various lighting conditions but the basic scene structure is still retained. Besides that, horizontal flipping was used as a form of geometric augmentation to mimic camera angle and pasture layout changes, thus lowering the model's awareness of spatial bias. All the augmentations were done randomly during training using *torchvision.transforms*. The validation images stayed the same so that the evaluation was always the same.

Proposed model architecture

The prediction framework that was created in this research is determined by a tailored convolutional neural network (CNN) which is aimed at drawing out spatial, textural and structural clues from pasture canopy images while still being computationally efficient. The core of the system is based on a modified ResNet-style architecture where the regular convolutional layers are substituted with depthwise-separable convolutions, thus allowing the factorization of the filtering into space and channel-wise portions. This process not only decreases the number of learnable parameters but also increases the capacity of computation without losing any of the features being expressed, thus making the architecture fit for processing large-scale field images.

In order to improve the learning of channel-level representations, the use of Squeeze-and-Excitation (SE) blocks was applied after certain convolutional stages. These blocks adjust the features of the model by taking into account the relation of different channels, which in turn boosts the network's ability to detect biologically significant signals like tonal gradients, leaf density and irregularities in pasture surface structure.

Besides the traditional convolutional features, the model also uses the Fourier feature projection, where the input image is changed through low-frequency sinusoidal encodings that are done before entering the regression head. This technique enables the network to sense the periodic and quasi-periodic vegetation patterns like tuft spacing, fine-scale grass texture and canopy oscillations, which would be tricky to show using spatial convolutions alone. The combination of the features obtained from the CNN and the Fourier-encoded representations result in a more powerful latent embedding for biomass estimation.

The final stage of this architecture is modeled by a multi-output regression head, which is denoted by fully connected layers, that predicts all five biomass constituents simultaneously. The transformation from the latent (X) to predicted values is expressed as in Eq. (4):

$$\hat{Y} = f\theta(X) = [\hat{y}_{DG}, \hat{y}_{DD}, \hat{y}_{DC}, \hat{y}_{GDM}, \hat{y}_{DT}] \quad \dots(4)$$

Where,

($\hat{y}_{DG}$), ($\hat{y}_{DD}$), ($\hat{y}_{DC}$), ($\hat{y}_{GDM}$), ($\hat{y}_{DT}$)= The forecast values for *Dry_Green_g*, *Dry_Dead_g*, *Dry_Clover_g*, *GDM_g* and *Dry_Total_g*, in that order, respectively.

The schematic diagram of the proposed CNN-SE-Fourier model forward-propagation sequence is summarized in Algorithm 1. Every architectural element plays a role in the performance of the system and the roles are complementary. The depthwise-separable convolution lowers the computational requirement and at the same time maintains the spatial detail which is an advantage when deploying the model in limited-resource environments. The Squeeze-and-Excitation blocks improve the ability to differentiate the features among the channels which in turn increases the model's sensitivity to the cues such as vegetation density and tonal variation that are of biological interest. Fourier feature projections allow capturing the functions in the frequency domain which aid in the capture of fine-scale texture and quasi-periodic canopy patterns that are hard to model with mere spatial convolutions due to their nature of being difficult to detect in spatially convoluted areas.

Algorithm 1: Forward Propagation of the Proposed CNN-SE-Fourier Biomass Estimation Model.

Input: RGB image (I).

Output: Predicted biomass vector ($\hat{Y}$).

Input normalization

- Resize the input image (I) to (400 × 200) pixels.
- Apply channel-wise normalization using Eq. (2):

$$I_{\text{norm}} = \frac{1 - \mu}{\sigma}$$

Backbone feature extraction

- Pass (I_{norm}) through successive convolutional blocks.
- In each block, apply depthwise-separable convolution, batch normalization and ReLU activation.
- Apply Squeeze-and-Excitation (SE) channel recalibration in selected blocks.
- Denote the extracted CNN feature map as (F_{cnn}).

Fourier feature encoding

(a) Apply a low-frequency sinusoidal projection to the input image:

$$F_{\text{fourier}} = \gamma(I)$$

Where,

$(\gamma(\cdot))$ denotes the Fourier encoding function.

Latent feature fusion

(a) Concatenate the CNN and Fourier features to obtain the fused latent representation:

$$X = [F_{\text{CNN}}; F_{\text{fourier}}]$$

Multi-output regression head

- Pass the fused representation (X) through fully connected layers.
- Generate simultaneous predictions for all biomass components using Eq. (4):

$$\hat{Y} = f_{\theta}(X) = [\hat{y}_{DG}, \hat{y}_{DD}, \hat{y}_{DC}, \hat{y}_{GDM}, \hat{y}_{DT}]$$

Return

Return the predicted biomass vector ($\hat{Y}$).

Training configuration and optimization

Model optimization was done by applying the Smooth L1 loss function, also known as the Huber loss, which gives advantages of robustness against noisy biomass measurements and at the same time combines the two forms of penalties by using the quadratic and linear penalty regions. For the different biomass components, the loss was calculated based on equation (5):

$$\mathcal{L}(y, \hat{y}) = 0.5 (y - \hat{y})^2 \text{ if } |y - \hat{y}| < 1, \text{ else } |y - \hat{y}| - 0.5 \quad \dots(5)$$

When necessary, a weighted loss formulation was applied so as to give more importance to the agronomic importance of the individual biomass components, according to equation (6):

$$L_{\text{total}} = \sum_{k=1}^5 w_k L(y_k, \hat{y}_k) \quad \dots(6)$$

The optimization was done with the help of the *AdamW* optimizer which separates weight decay from gradient updates to enhance stability. The early learning rate and weight decay coefficient were set by trial and error and a

ReduceLROnPlateau scheduler was used to lower the learning rate automatically when the validation performance stopped improving. Training was done in mini-batches and gradient clipping was active to avoid instability that might be caused by large gradient updates in the deeper layers. Also, dropout was used in the fully connected layers to fight overfitting.

All pre-processing, training and evaluation procedures were applied consistently across experiments to ensure methodological transparency and reproducibility.

RESULTS AND DISCUSSION

The findings presented in this part are all drawn from the validation set of 20% that was held out, which was prepared by a prefix-based stratified split to prevent any data leakage. The analysis comprises the trends of training and validation losses, overall regression metrics, performance by component and predicted-versus-actual relationships, along with qualitative examples. This provides a comprehensive and neutral assessment of the model's capability to measure pasture biomass under various field conditions.

Training and validation curves

Fig 1(a) shows stages of the training of the proposed model. The Smooth L1 loss decreases steadily over the epochs for training as well as validation data. This indicates that the model is training really well and is also able to optimize really well. The two lines also tend to be equal; they do not deviate much from each other, which indicates that the methods of preventing overfitting, including data augmentation, dropout, gradient clipping and using AdamW optimization, have really helped in preventing overfitting in this model because of the biomasses present in the data, as data in real-world images keeps changing, which leads to noise in ground truth values.

For further evaluation of predictive performance, Fig 1(b) also shows a scatter plot of predicted versus measured biomass for all plant components together. The data points lie very close to the line of equality, which indicates that the model is well calibrated for both low and high biomass conditions. Deviations for a few high biomass

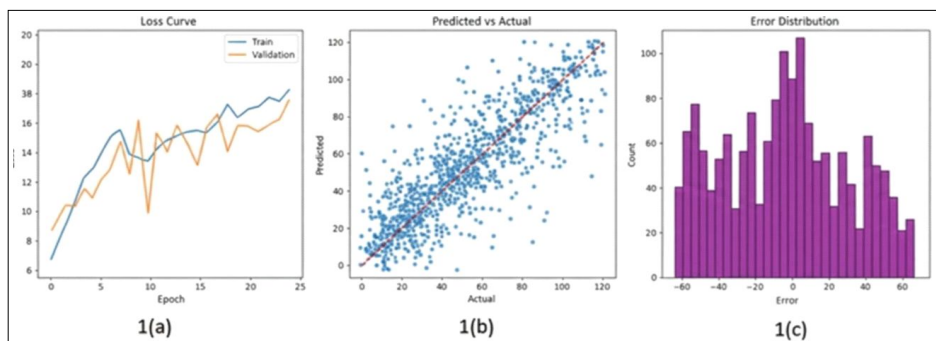


Fig 1: Training loss, predicted vs. actual biomass and residual error distribution for the proposed model.

samples are biologically reasonable as they account for natural variations in dense pasture vegetation.

Error distribution in Fig 1(c) is symmetrical, having an approximately central value of zero, which indicates that it does not introduce bias in either overestimation or underestimation. The data distribution is compact, having only a few data points as possible outliers, which further confirms validity in the results produced by it. From all the above analyses, it is clear that a stable model is developed for multi-output biomass estimation in pasture environments.

Quantitative performance evaluation

For assessing how well the CNN-SE-Fourier model predicted, regression analysis metrics were employed. The Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the weighted coefficient of determination metrics, in this case, were employed for regression analysis. The calculations of the metrics for regression analysis were conducted using the validation split, which is set aside to provide an accurate indication of generalization for all five biomass fractions. The results of this analysis are presented in Table 1.

The value of validation loss for the model came out to be 6.3722, whereas the total MSE was 124.4405, causing RMSE to be 11.159. This, in turn, shows that there was a strong predictive agreement with the biomass observations from the ground truth. The weighted value of 0.8133 is an indication that the model explains more than 81% of the variance in biomass measurements which, in fact, is a proof of its capacity in capturing structural and spectral cues present in pasture images. The global MAE is different across components, due to different biomass scales, but the overall error behavior remains the same as that of field-level variability which is typically observed in pasture systems.

Introducing Smooth L1 (Huber) loss (Eq. 5) was a pivotal factor in the model's characterization of being able to resist high-variance samples and measurement noise. It is the combination of the quadratic and linear error regions that makes the optimization process easier and prevents large errors from taking over the training signal, which is very crucial for the real-world biomass datasets that are diverse and noisy.

The consistency of results across biomass components and validation metrics indicates stable model behaviour rather than reliance on isolated favourable cases.

To evaluate the robustness of the proposed method thoroughly, we assessed its performance in comparison with standard baseline models, particularly with a mean predictor, linear regression and random forest regressor, all using the same validation split. Table 2 shows that the CNN-SE-Fourier model greatly exceeds all the baseline methods getting R^2 of 0.813 while random forest and linear regression receive 0.304 and 0.145 respectively. The huge reduction in RMSE and MAE implies that the proposed architecture is capable of capturing the spatial, textural and structural information found in pasture images which are

not sufficiently represented by the traditional regression-based methods.

Component-wise prediction

In addition to the overall performance reported in Section 3.2, a component-wise evaluation was performed to evaluate the model's behavior for the five biomass outputs individually. The RMSE and MAE values obtained from the validation set for each biomass component are summarised in Table 3. These metrics are a clear indication of how the prediction accuracy varies among different components that are affected by dynamic range, texture complexity and visual separability.

Due in part to its high variability, *Dry_Green_g* is considered a good proxy for pasture biomass. Therefore, only this component is subjected to detailed visual evaluation. Fig 2 shows the true values compared with predicted values for *Dry_Green_g* and it is clear that there is a strong alignment along the 1:1 line even though the green biomass in pasture systems is naturally wide spread. In Fig 3, quite a few representative images are shown, which based on their appearance and structure, are further proof of model's capability of detecting and depicting the green vegetation cover.

However, for the residues which comprise *Dry_Dead_g*, *Dry_Clover_g*, *GDM_g* and *Dry_Total_g*, the final numbers are still available in Table 2. The stability of the predictive behavior for these components is furthermore indicated by the consistent error magnitudes, which are in

Table 1: Overall regression performance on the validation set.

Metric	Value
Training loss	6.95
Validation loss	6.3722
MSE	124.4405
RMSE	11.159
Weighted	0.8133

Table 2: Comparison of the proposed CNN-SE-fourier model with standard baseline regression models on the validation set.

Model	RMSE ↓	MAE ↓	R^2 ↑
CNN-SE-fourier (Proposed)	11.16	6.88	0.813
Random forest	21.53	15.99	0.304
Linear regression	23.87	17.86	0.145
Mean predictor	25.82	19.96	-0.000

Table 3: Component-wise RMSE and MAE for biomass prediction.

Biomass component	RMSE	MAE
Dry_green_g	34.6171	25.1508
Dry_dead_g	15.4864	11.8623
Dry_clover_g	13.1856	6.7593
GDM_g	34.4465	25.1166
Dry_total_g	38.9721	29.3226

line with both the domain expectations and the inherent variation in ground-truth measurements.

Limitations

Even though the proposed model is generally strong, it still has certain limitations.

- (i) The model's ability to extract more than one characteristic from vegetation at a time, such as chlorophyll and moisture will be restricted by the sole use of RGB images. This can lead to a case of underestimation in high-biomass conditions.
- (ii) The dataset is composed of a small number of extreme biomass samples, thereby restricting the overall applicability of the model apart from even the areas where Smooth L1 loss offers robustness.
- (iii) Data from one geographic region might result in a model that is not able to adapt well to other areas or seasons with different pasture types and environmental conditions affecting the latter's transferability.
- (iv) RGB images of overlapping and dense canopies may be hard to visualize and thus, precise estimation can be sometimes difficult.

- (v) The model yields outputs that are deterministic and there is no uncertainty quantification, hence, in operational settings, decision-making confidence may get affected.

Discussion and implications for precision agriculture

The study shows that robust estimation of pasture biomass is feasible using low-cost sensing systems and miniaturized deep learning systems even in practical field settings. The outcomes indicate that the available CNN-SE-Fourier model is the one that best predicts the biomass of different pasture condition and its reliability is for sure. The strong weighted score (0.8133) and consistent component-wise performance suggest that the model does a very good job in spotting the visual cues of live and dead biomass, even in the case of the natural grasslands' heterogeneity. These findings demonstrate robust performance within the evaluated pasture conditions and dataset. The higher variability of the predictions in the case of *Dry_Green_g* and *Dry_Total_g* indicate that they are the more complex and dynamic components of the whole process, while *Dry_Clover_g* and *Dry_Dead_g* are the least variable and more stable ones with tighter error bounds.

The operational aspect of the model's power to predict a number of biomass fractions from simple RGB imagery simply points to its great importance in the field of precision agriculture. Such a system can assist in the management of grazing by allowing quick and non-destructive assessments of feed availability, which in turn cuts down the need for labor-intensive field sampling. The lightweight architecture and stable learning behavior also render the approach suitable for low-cost devices, which can later be incorporated into mobile or UAV-based workflows. While the underlying design is not specific to a single environment, extending deployment across different regions, seasons, or pasture types will require additional validation.

In conclusion, this study highlights the potential of compact deep-learning models, which are augmented with attention as well as frequency features, to produce pasture insights that are ready for action. The incorporation of multi-spectral inputs or temporal data can take such systems to the level of being scalable.

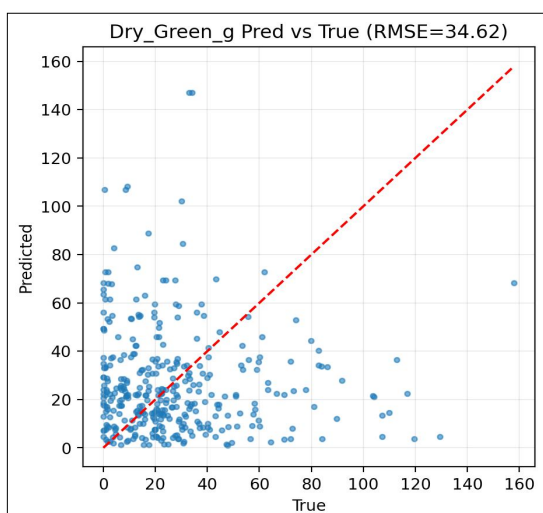


Fig 2: Predicted versus true dry green g values with the 1:1 reference line (RMSE = 34.62 g).

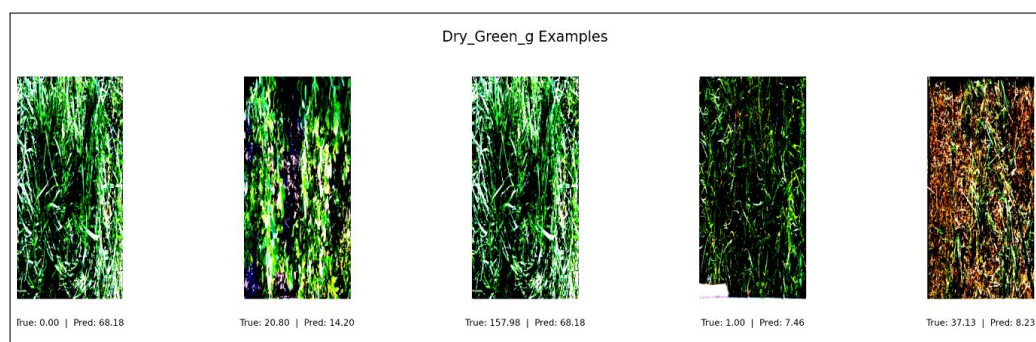


Fig 3: Example dry green g image patches with corresponding true and predicted biomass values.

Such extensions are therefore identified as promising directions for future research rather than conclusions drawn from the present study.

CONCLUSION

A CNN-SE-Fourier architecture for multi-output pasture biomass prediction with RGB and metadata was presented as a very light-weight model in this study. Predicted performance of the model was really good with the weighted of 0.8133 plus stable accuracy for the five biomass categories. The combination of depthwise separable convolutions, Squeeze-and-Excitation channel reweighting and Fourier feature injection played a major role in the strong feature extraction under different field conditions.

The findings assure that it is possible to get accurate estimates with very inexpensive image data, thus providing a good alternative to the traditional sampling method that is so labor-intensive. This means that the very crops that the farmers cannot allow go to waste because of their timely projected grazing can now be used and the pasture yield, moreover the non-destructive, scalable monitoring of vegetation dynamics, will not lose its value. Even though in the case of the extreme biomass values, slight underestimations happened, the overall performance indicates a strong potential for operational deployment.

Future enhancements could vary from the use of multispectral or temporal data, to exploring transformer-based encoders, to even creating uncertainty-aware models for prediction. These could help in sustainable pasture management by AI tools, not only in the short term but also in the longer term, by improving generalization capabilities from one region to another as well as from different seasons to different seasons.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Informed consent

No animal or human subjects were involved in this study and therefore ethical approval and informed consent were not required.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

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