Uncertainty and Feature-Based Weighted Loss for 3D Wheat Part Segmentation

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Abstract: Deep learning techniques and point clouds have proved their efficacy in 3D segmentation tasks of objects. Nevertheless, the accurate plant organ segmentation is a formidable challenge due to their complex structure and variability. Furthermore, presence of over-represented and under-represented parts, occlusion, and uneven distribution complicates the 3D part segmentation tasks. Even though deep learning techniques often exhibit exceptional performance, they also face challenges in applications where accurate trait estimation is required. To handle these issues, we propose a novel uncertainty and feature based weighted loss that incorporates uncertainty metrics and features of the plant or crop. We use Gradient Attention Module (GAM) with PointNet++ baseline to validate our approach. By dynamically introducing uncertainty and feature scores into the training process, it promotes more balanced learning. Through comprehensive evaluation, we illustrate the advantages of UFL (Uncertainty and Feature based Loss) as compared to standard CE (Cross entropy loss) with our own constructed real Wheat dataset. The outcomes demonstrate consistent improvements in Accuracy (ranging from 0.9% to 4.2%) and Ear mIoU (ranging from 1.8% to 15.3%) over the standard Cross-Entropy (CE) loss function. As a result, our work contributes to the development of more robust and reliable segmentation models. This approach not only pushes forward the boundaries of precision agriculture but also has the potential to influence related areas where accurate segmentation is pivotal.

1 INTRODUCTION

Component phenotyping refers to the measurements of different plant organs i.e., leaf and stem length, leaf width, leaf area etc. These measurements are essential markers for tracking plant development and forecasting yield (Shen et al., 2024). The extraction of morphological and architectural traits are critical for high throughput plant phenotyping, which requires precise segmentation of plant organs. Manual methods are dominant, quite labor intensive, and unable to meet the requirements of analysis of large populations (Minervini et al., 2015). In the past few years, computer vision and deep learning techniques have facilitated plant phenotyping (Mochida et al., 2018). With the development of point cloud based deep learning networks i.e., PointNet (Qi et al., 2016) and its enhanced variant PointNet++ (Qi et al., 2017), remarkable progress has been made in 3D point-based deep neural networks. Besides its proliferation, current deep learning approaches on point cloud data are usually limited to synthetic datasets i.e. ModelNet40 and ShapeNet (Chang et al., 2015), S3DIS (Armeni et al., 2016) and their application of 3D real world data for plant segmentation tasks is at its infancy. One of the underlying reasons for their limited application in plant domain is the lack of rich annotated datasets and their labeling process takes a lot of manual power (Chaudhury et al., 2020). Real datasets, particularly those concerning plants, exhibit significant differences from their synthetic counterparts. In response, different architectures have been developed for plant segmentation tasks (Turgut et al., 2022), (Ghahremani et al., 2021), (Li et al., 2022). These efforts highlight the ongoing advances in tailoring segmentation models to the unique challenges presented by real agricultural data. Despite these innovations, achieving precise estimations remains a challenge. Incorrect classification leads to erroneous

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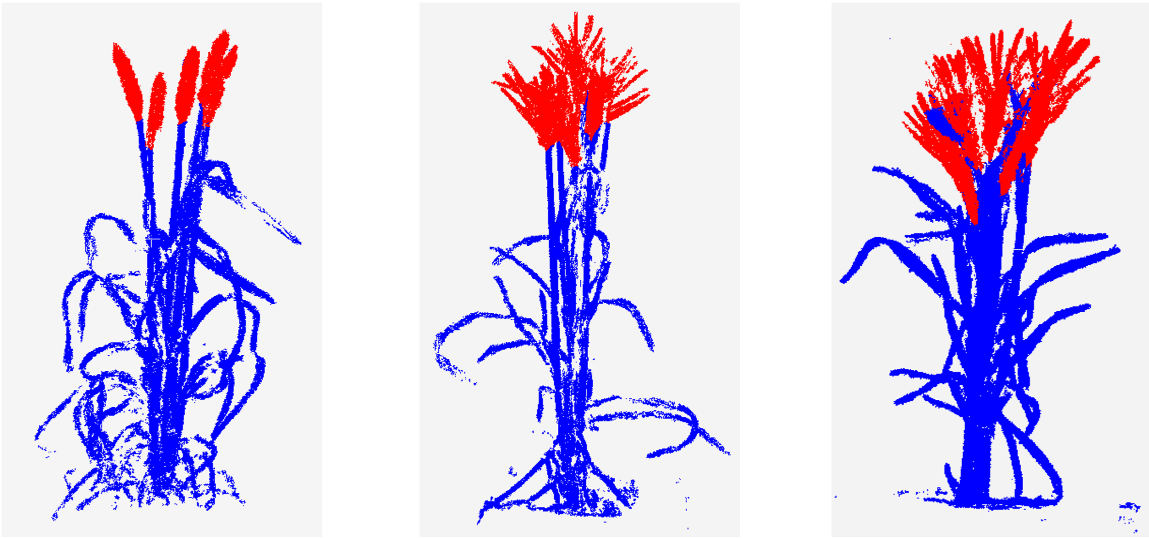
estimates of the traits, which could significantly influence agricultural strategies and outcomes.

Previous research studies (Leibig et al., 2016; Mukhoti et al., 2021; Kong et al., 2023) demonstrate the significance of uncertainty quantification in improving the robustness of model predictions. For instance, (Wang et al., 2020) discusses incorporation of uncertainty measure into their technique significantly enhances both the accuracy and effectiveness of their approach. Similarly, uncertainty quantification concept is employed to enhance segmentation tasks in autonomous driving applications, ensuring both safety and reliability (Sun et al., 2024; Landgraf et al., 2024). The uncertainty estimates are distinct from softmax probabilities, by revealing the model's confidence in its predictions. These estimates help identify potential uncertainties within the data that could lead to incorrect outcomes. Though utilization of uncertainty is explored in segmentation tasks, it is under explored in the agricultural domain as compared to its frequent application in medical and automotive domains. In this work we propose a novel UFL (Uncertainty and Feature based Loss) to bridge this gap that utilizes uncertainty estimation during training and integrate features of the wheat crop into the loss function to enhance the segmentation of the models. Primarily, we leverage the model's uncertainty estimates to quantify the confidence levels of its predictions and then incorporate important features. By integrating feature importance analysis with uncertainty quantification into a hybrid scoring mechanism within our loss function, our approach adeptly identifies critical features, such as wheat ear (spike) counts, that influence model predictions, while simultaneously quantifying the associated uncertainties. We conduct extensive experiments with our constructed Wheat dataset that has three different varieties i.e. Paragon, Gladius and Apogee to exhibit the effectiveness of our technique using GAM (Hu et al., 2023). The motivation is that plants have quite complex structures and they varied according to their environmental conditions. Our findings demonstrate that innovative integration of the loss function and the critical features significantly enhances the robustness of segmentation tasks. Precise and accurate segmentation is quite crucial in plants to make estimates about yield and making different agricultural decisions. Lastly, we exemplify ablation studies, limitations and future work of our study.

2 RELATED WORK

In the domain of segmentation and 3D object detection, numerous research studies have employed the concept of uncertainty. We offer a summary of significant studies that utilize uncertainty aware techniques for computer vision tasks across different domains. Over past few decades uncertainty estimation has been prevailing topic of researchers in image processing tasks. (Blundell et al., 2015) introduced the use of a Gaussian distribution over network weights, characterizing each weight with a mean and variance. However, the discussed technique was not optimal for deep learning architectures due to a large number of model parameters. With similar motivation, (Gal and Ghahramani, 2016) suggested using Monte Carlo (MC) dropout to apply dropout techniques for variational inference. During training, neurons are randomly dropped, creating a Bernoulli distribution over the network weights. While testing, the same image is fed through the network multiple times with dropout, allowing for estimation of uncertainty from these outputs. Quantification of uncertainty is exercised in segmentation and object detection tasks. This approach is especially critical in autonomous driving scenarios, where safety is a critical issue, as incorrect predictions can result in severe consequences.

(Landgraf et al., 2024) has addressed this issue with proposition of uncertainty aware segmentation that will make estimates about the uncertainty during training. On the basis of measures of uncertainty, pixel-wise weight is attached to the regular cross entropy loss to improve the segmentation performance. With similar aim, panoptic segmentation is achieved based on calibration of per pixel uncertainty estimates (Sirohi et al., 2022). This study has covered semantic and instance segmentation. In another study, uncertainty estimation and segmentation module is proposed to boost the segmentation performance in uncertain regions by exploiting the uncertainty maps (Bian et al., 2020). To handle imbalance issue in segmentation tasks, (Bischke et al., 2018) has suggested adaptive uncertainty weighted class loss to improve the outcomes of neural network architectures. A fuzzy uncertainty based method has been proposed to expose out of distribution data samples for semantic segmentation (Lin et al., 2023). The above discussed technique integrates test-time augmentation and Monte Carlo dropout with a trained segmentation model to generate multiple predictions, capturing both data and model uncertainties. These predictions form interval fuzzy sets, which are used to calculate an image-level uncertainty score for identifying out-of-distribution (OOD) samples. (Sun et al., 2024) has explored label uncertainty or annotated uncertainty information, for precise object detection in 3D data. In the field of healthcare, (Leibig et al., 2016) has utilized uncertainty information for disease detection.



Paragon Gladius Apogee

Figure 1: Annotated 3D models of three wheat cultivars.

Authors have employed the concept of Bayesian uncertainty that works better than other alternatives. The findings indicate that incorporating uncertainty data into decision-making processes can enhance diagnostic accuracy. Another study has employed uncertainty map to address the issue of unreliable segmentation (Tang et al., 2022). To effectively extract meaningful features and harness the potential of uncertainty, the researchers introduced an uncertainty-guided module. This module improves the model's ability to discern subtle features that are often overlooked in standard segmentation approaches. In addition to autonomous driving and medical imaging, research has also been conducted in synthetic aperture radar (SAR) applications (Haas and Rabus, 2021). This study evaluates uncertainty measurements to assess real-world quality control performance. It utilizes softmax scores for uncertainty estimation, which have been shown to offer more practical insights compared to Bayesian methods.

3 METHODOLOGY

3.1 Dataset Description

The three wheat varieties—Paragon, Gladius, and Apogee were grown in an ecologically controlled Smarthouse at the National Plant Phenomics Centre (NPPC), Aberystwyth University, under experiment reference W048. The plants were cultivated on a conveyor system that was computer controlled, and the soil water levels were changed to sustain either a moderate drought or well-watered circumstances. Every plant was given a unique barcode that was connected to all of the data it had gathered and put on an RFID-tagged carriage. Over the course of 44 days, a 360-degree imaging strategy obtained 74 multi-view photos per plant every day. The 3D models were reconstructed using open source photogrammetry software COLMAP (Schönberger and Frahm, 2016; Schönberger et al., 2016). After 3D reconstruction, the point cloud data was labelled using package CloudCompare (Girardeau-Montaut, 2012). The segment function in the package was employed to divide the plant into two parts and then the parts were annotated using the Scalar function. Figure 1 depicts the labelled point clouds. The red color is labelled with '1' that represents ear part (spikes) and the blue part is labelled with '0' representing non-ear (leaves and stems) part. We have downsampled each sample to 2048 points for the sake of computational feasibility.

Table 1: Dataset descriptions for different wheat categories.

Variety	**Total**	**Train**	**Val**	**Test**
Paragon	385	308	24	53
Gladius	371	296	25	50
Apogee	547	436	32	79
Wheat (All cultivars)	1303	1040	81	182

Despite the fact that they belong to the Wheat category, the three cultivars show quite different characteristics and architectures:

- Paragon: Mostly made up of leaves with a few tall ears rising above them.
- Gladius: The species distinguished by having more ears that are partly hidden beneath the fo-

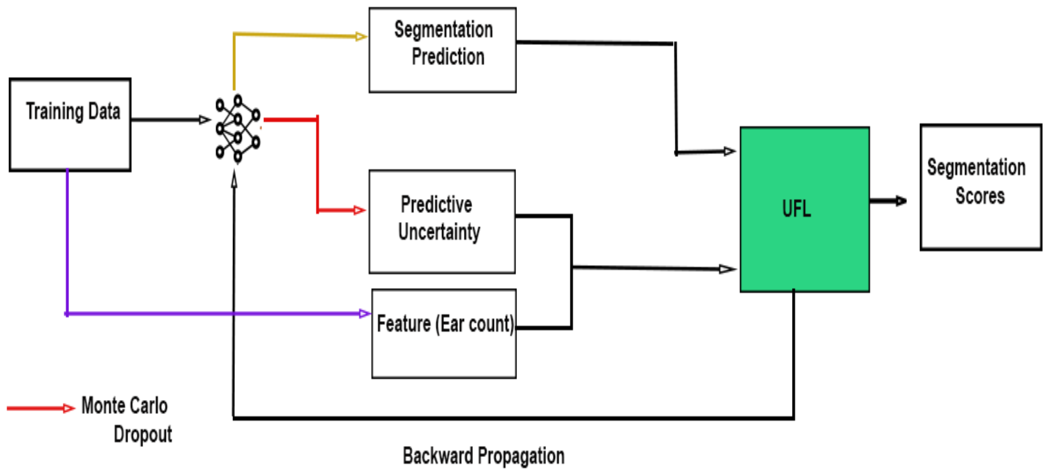


Figure 2: A schematic overview of the UFL training process, which incorporates predictive uncertainties from a Monte Carlo Dropout (MC-Dropout) and Features of plant to improve segmentation performance.

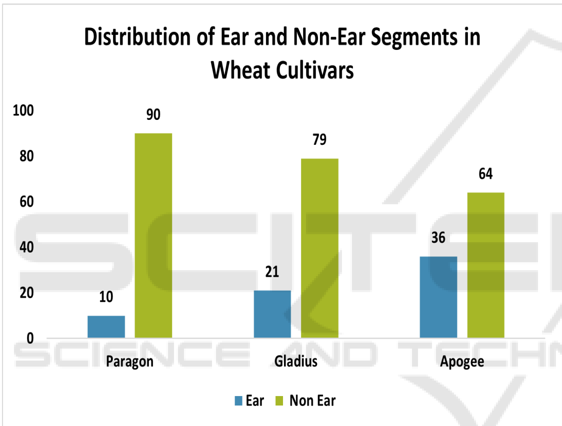


Figure 3: Distribution of Ear and Non-Ear parts in three wheat cultivars.

liage.

- Apogee: A super dwarf with a high ear-to-leaf ratio that is known for its quick cycling.

Table 1 illustrates the wheat dataset with all training, validation, and test samples used in this research study. Figure 3 illustrates the proportion of ear points and non-ear points of each wheat variety. Paragon exhibits a notably smaller proportion of ear points compared to those of Gladius and Apogee. Gladius has a reasonable number of ear points, while Apogee shows a significantly larger proportion, highlighting the variability and imbalance in ear point distribution across these varieties.

3.2 Proposed Approach

The core idea of our approach is to incorporate predictive uncertainties and plant specific feature together into the training process to enhance the accuracy of part segmentation of crops or plants. The method introduces an uncertainty and feature based loss function, which enhances the deep learning architecture's ability to prioritize learning from samples with high uncertainty or significant features. The proposed approach allows the model to focus on more challenging data, improving overall learning efficiency and model robustness. This approach introduces two primary enhancements into the training process:

1. Hybrid Score Calculation: During training, Monte Carlo Dropout is exploited that measures the uncertainty (u_i) in prediction of the samples. A hybrid score is calculated that integrates feature (e_i) i.e. ear count (wheat spikes) in our case. This score ensures that samples with both high uncertainty and significant feature attributes are weighted appropriately.
2. Weighted Loss: We employ hybrid score as weights in the loss function so that the model is encouraged to focus on more uncertain and feature rich samples to facilitate effective learning.

Figure 2 represents the UFL computation process.

3.2.1 Architecture

We have adopted Gradient Attention module (GAM) (Hu et al., 2023) with baseline PointNet++ for point cloud analysis for our proposed technique. We integrate the Gradient Attention Module (GAM), which is designed to focus the network's attention on crucial features within the data, potentially improving the accuracy and efficiency of segmentation. The incorporation of GAM with PointNet++ aims to explore whether this attention mechanism can refine the model's output by providing more focused and relevant feature analysis, especially for complex plant structures. The network utilizes gradient information in the neighborhood and converts that information into explicit representation. It is the first to incorporate gradient data into the vector of locally aggregated descriptors for point cloud neighborhood features. The results show that the module has effectively boost performance of the different state-of-the-art methods.

3.2.2 Uncertainty and Feature Based Weighted Loss

In contrast to the conventional utilization of Monte Carlo Dropout, our proposed approach extends its applicability to the training phase. During each batch of the training phase, we execute λ iterations to produce λ segmentation samples in order to measure uncertainties of the samples. The essential idea is that the differences between the model's successive predictions reflect its confidence level, which is a measure of epistemic uncertainty. The high variation in these predictions indicates a reduced confidence in the model's outputs, implying that the data poses challenges for accurate identification by the model. This variability acts as a direct signal of uncertainty, making it possible to identify samples with significant uncertainty. Gradients are deactivated during this computational phase to prevent them from affecting the backward propagation process. The ultimate goal of UFL is to enhance the standard categorical cross-entropy loss, which is articulated as follows:

The modified uncertainty feature weighted loss function can be expressed as:

$$L_{\text{UFL}} = -\frac{1}{M}\sum_{i=1}^{M} w_i \sum_{j=1}^{K} y_{i,j}\log(q_{i,j}),$$

where:

- M is the total number of samples,
- K is the number of classes,
- w_i represents the weight for the i-th sample,
- $y_{i,j}$ is the ground truth probability for the i-th sample and j-th class,
- $q_{i,j}$ is the predicted probability for the i-th sample and j-th class.

Sample Wise Weight:
In our technique, the sample weight w_i is influenced by uncertainty scores and the plant features, notably the 'ear' count of wheat. The weight for each sample is formulated as follows:

$$w_i = \alpha \cdot e_i + \beta \cdot u_i,$$

where:

- α and β are parameters that modulate the contributions of the 'ear' feature importance (e_i) and uncertainty (u_i) respectively.
- e_i represents the 'ear' feature importance for sample i
- u_i denotes the uncertainty associated with sample i, reflecting the confidence level of the measurements or predictions.

e_i and u_i have quite disparity in the scale so we have chosen min-max normalization to ensure that these inputs are comparable and can contribute appropriately to the model's decision making process. This step will enhance the network's ability to integrate these metrics effectively, leading to more accurate and reliable segmentation predictions. α and β control the weights of the loss function. We have presented experiments to investigate the impact of these parameters on the performance of deep learning neural network architecture in the next section.

3.3 Experiments

In this section, we undertake a comprehensive series of experiments to validate the effectiveness of integrating predictive uncertainties into the training process.

3.3.1 Experimental Set up

Training: The network is trained for 150 epochs with a batch size of 8 with 2048 points in each point cloud. All the experiments are conducted utilizing the PyTorch deep learning framework, leveraging the computational power of an NVIDIA GPU with 12 GB VRAM. For all training procedures, we utilize a Stochastic Gradient Descent (SGD) (Robbins, 1951) optimizer configured with an initial base learning rate of 0.001, a momentum of 0.9, and a weight decay of 0.0001. The number of segmentation sample λ is set to 5 by default. All experiments are evaluated on Paragon, Gladius and Apogee i.e. Wheat varieties. For quantitative evaluations, we primarily report the mean Intersection over Union (mIoU), and Accuracy.

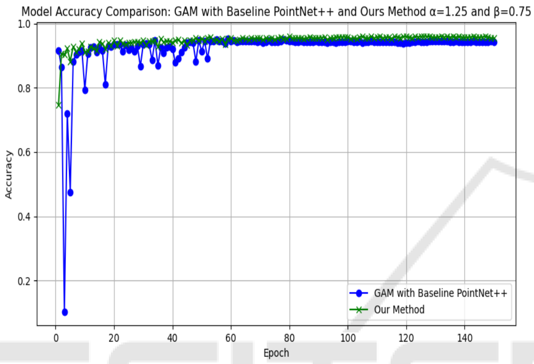
3.3.2 Quantitative Results

We have employed GAM module with PointNet++ (Qi et al., 2017) as baseline.

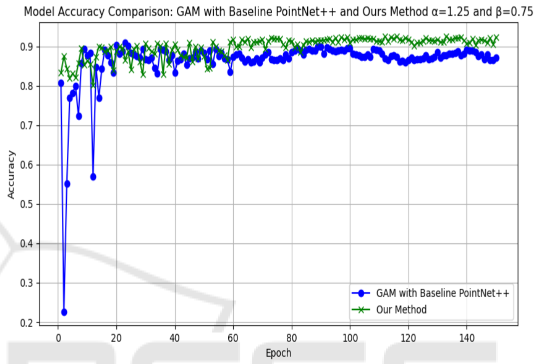
Table 2 shows a notable improvement in segmentation accuracy and mean Intersection over Union (mIoU) when we apply our Uncertainty and feature

Table 2: Comparative Study of Segmentation Methods Across Three Datasets.

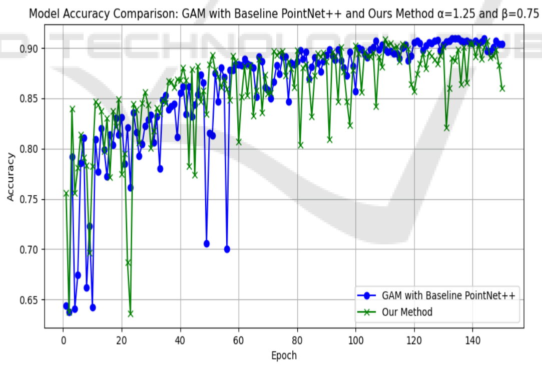
Dataset	GAM (Baseline PointNet++)	Accuracy	mIoU	Non-Ear mIoU	Ear mIoU
Paragon	CE	0.917	0.650	0.907	0.392
	UFL $\alpha = 1.25, \beta = 0.75$	**0.959**	**0.750**	**0.956**	**0.545**
	UFL $\alpha = 1.5, \beta = 1$	0.951	0.685	0.942	0.422
Gladius	CE	0.892	0.712	0.870	0.554
	UFL $\alpha = 1.25, \beta = 0.75$	**0.919**	**0.771**	**0.904**	**0.637**
	UFL $\alpha = 1.5, \beta = 1$	0.898	0.741	0.880	0.603
Apogee	CE	0.908	0.818	0.869	0.768
	UFL $\alpha = 1.25, \beta = 0.75$	0.917	0.831	**0.884**	0.782
	UFL $\alpha = 1.5, \beta = 1$	0.915	0.830	0.879	**0.783**



(a) Paragon Dataset



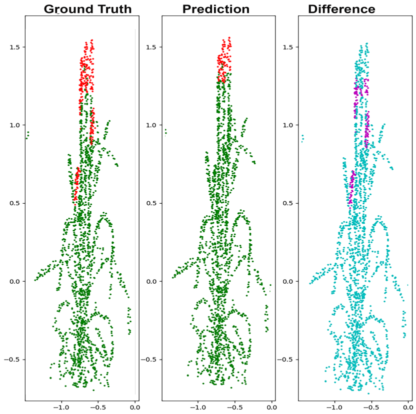
(b) Gladius Dataset



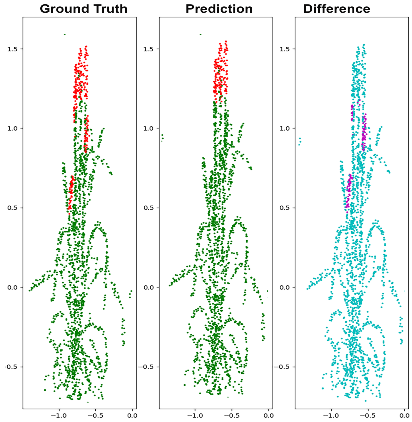
(c) Apogee Dataset

Figure 4: Model Accuracy Comparison: GAM with baseline PointNet++ vs. Our Method for three different datasets (Paragon, Gladius, Apogee). Each graph shows the segmentation accuracy across the training epochs.

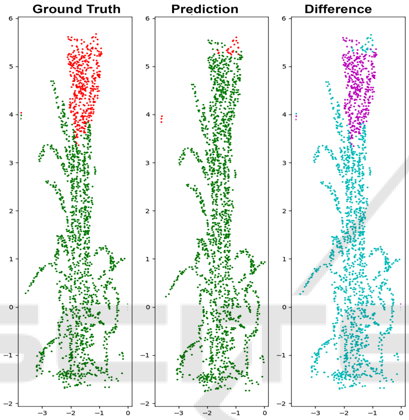
based loss (UFL) as compared to traditional Cross Entropy (CE) loss across all the datasets. Particularly α = 1.25 and β = 0.75 consistently outperforms other configurations, suggesting that optimal balance between uncertainty and feature values assist in model learning. This configuration leads to substantial gains in both Ear mIoU and Non-Ear mIoU, underlining its effectiveness in differentiating between more and less challenging segmentation areas. Paragon accuracy rose from 0.917 to 0.959 and mIoU witnessed a jump of 10% in the figures. Gladius saw slight improvements in Accuracy but there is rise of 6% in mIoU. Although Apogee is the one wheat variety that is quite complex and the results refined from 0.908 accuracy to 0.917 but the Ear mIoU has a slight decline as compared to the scenario when α = 1.5 and β = 1, highlighting the trade-offs involved in optimizing these parameters. Figure 4 presents the training



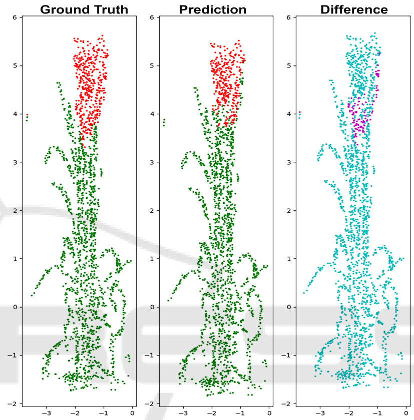
(a) Paragon (Base Method)



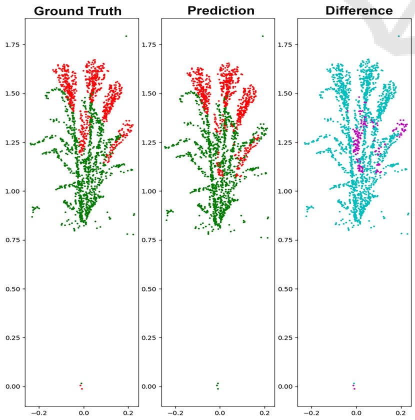
(b) Paragon (Ours Method , $\alpha = 1.25, \beta = 0.75$)



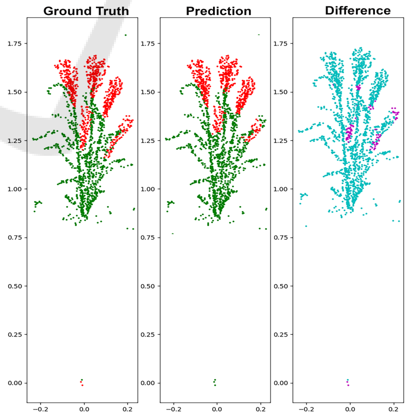
(c) Gladius (Base Method)



(d) Gladius (Ours Method, $\alpha = 1.25, \beta = 0.75$)



(e) Apogee (Base Method)



(f) Apogee (Ours Method, $\alpha = 1.25, \beta = 0.75$)

Figure 5: Comparison of segmentation results on the Paragon, Gladius, and Apogee datasets. Each dataset shows a baseline and our method view to illustrate the effectiveness of the proposed strategy. In the visual representations, the ear part is marked in red, while the non-ear part is depicted in green for both the Ground Truth and Prediction columns. Correct predictions are highlighted in cyan, whereas magenta is used to indicate misclassifications. This color-coded approach helps to clearly delineate the improvements our method brings in accurately segmenting the ear and non-ear components across different wheat varieties.

Table 3: Segmentation Methods Across Three Datasets with GTNet.

Dataset	GTNet	Accuracy	mIoU	Non-Ear mIoU	Ear mIoU
Paragon	CE	0.927	0.662	0.923	0.400
	UFL $\alpha = 1.5, \beta = 1$	**0.932**	**0.676**	**0.929**	**0.425**
	UFL $\alpha = 1.25, \beta = 0.75$	0.931	0.658	0.929	0.388
Gladius	CE	**0.886**	0.667	**0.873**	0.460
	UFL $\alpha = 1.5, \beta = 1$	0.881	**0.721**	0.854	**0.588**
	UFL $\alpha = 1.25, \beta = 0.75$	0.862	0.660	0.839	0.481
Apogee	CE	0.811	0.668	**0.751**	0.584
	UFL $\alpha = 1.5, \beta = 1$	0.817	**0.688**	0.742	**0.633**
	UFL $\alpha = 1.25, \beta = 0.75$	**0.819**	0.686	0.748	0.628

accuracy of our method with each variety. The figures demonstrate that our proposed approach yields a marked improvement in accuracy over the baseline method. This enhancement is evident across various metrics and scenarios, highlighting the effectiveness of integrating feature importance and uncertainty quantification into the segmentation process.

Furthermore, an increase in values of α =1.5 and β = 1 leads to decline in certain performance metrics as compared to previous discussed parameter settings but the overall results consistently surpass those achieved using the traditional Cross-Entropy (CE) loss. This trend is particularly evident across multiple datasets, where even with higher parameter values, the UFL method demonstrates superior capability in handling complex segmentation tasks. This suggests that careful tuning of these parameters can lead to optimized model performance enabling more accurate segmentation.

3.3.3 Qualitative Results

Figure 5 presents qualitative results of baseline and our proposed approach. We have chosen the best results of our technique. It is clear from the results for Paragon and Gladius that the number of misclassifications has decreased. Although it is more challenging to assess the impact for Apogee due to its complex wheat variety, quantitative data indicate substantial improvements for Apogee as well.

3.3.4 Comparative Study with GTNet

To further demonstrate its potential, we carry out a comparative study between our proposed technique with our deep learning network architecture with GTNet (Zhou et al., 2024), which is another network architecture that integrates the Transformer and Graphs based approaches. It features a Local Transformer, which utilizes intra-domain cross-attention, and a Global Transformer that employs global self-attention to extract local and global features efficiently. We have opted this model due to its strength in segmentation tasks. Table 3 illustrates the impact of our loss function as compared to the basic CE loss function.

Performance in Paragon has improved with α =1.5 and β = 1 with the average mIoU experiencing a slight increase from 0.662 to 0.667 but the Ear mIoU saw a slight dip. Similarly, Gladius has shown enhanced performance under the same settings, with its mIoU rising from 0.667 to 0.721. Apogee also displays a similar trend in performance, with its mIoU improving from 0.668 to 0.688 as compared to the baseline loss function. However the segmentation accuracy in each variety has a slight improvement. For instance, Paragon accuracy have a rise from 0.927 to 0.932 but this is not the same with Gladius which has seen a certain drop in this metric. Apogee is one variety that has seen enhancement in the results of segmentation accuracy from 0.811 to 0.817. We have observed that while both parameter settings are effective, they do not achieve results as impressive as those obtained with GAM under similar conditions.

3.4 Ablation Studies

In addition to the quantitative and qualitative results above, we also perform multiple ablation studies below.

Impact of α and β : The α controls uncertainty scores and β have an impact on feature i.e. ear count in our case. In this section we have evaluated the impact of α and β with varied values to explore their impact on the model's performance. These parameters are crucial to understand the sensitivity of our deep learning architecture to these adjustments. Interestingly, some parameter settings may lead to decrease in performance. Table 4 presents the performance of the architecture with our proposed technique. α =1 and β =1 consistently outperformed the CE baseline across all datasets. But with another setting (α =1.4 and β

Table 4: Ablation studies of Segmentation Methods Across Three Datasets.

Dataset	GAM (Baseline PointNet++	Accuracy	mIoU	Non-Ear mIoU	Ear mIoU
Paragon	CE	0.917	0.650	0.907	0.392
	UFL $\alpha = 1, \beta = 1$	**0.954**	**0.714**	**0.951**	**0.477**
	UFL $\alpha = 1.4, \beta = 0.9$	0.949	0.699	0.946	0.453
Gladius	CE	0.892	0.712	0.870	0.554
	UFL $\alpha = 1, \beta = 1$	**0.911**	**0.764**	**0.895**	**0.634**
	UFL $\alpha = 1.4, \beta = 0.9$	0.888	0.706	0.873	0.539
Apogee	CE	0.908	0.818	0.869	0.768
	UFL $\alpha = 1, \beta = 1$	**0.910**	**0.830**	0.883	**0.776**
	UFL $\alpha = 1.4, \beta = 0.9$	0.910	0.818	0.876	0.761

= 0.9) of optimized parameters the performances face a slight decrease especially in case of Apogee. These findings highlight a critical balance in the parameter settings within our UFL framework.

Increasing each parameter beyond threshold can impact model's performance. So an optimal parameter setting is pivotal that provides substantial improvements over baseline without compromising model's robustness. In this ablation a small change in parameters have an influence on segmentation accuracy and mIoU. To exemplify this, when α has an increase of 0.4 and β has very small change of 0.1 the performance of the model decreases in each wheat variety. Paragon saw a decline of 5% in segmentation accuracy and a similar trend is followed in Gladius where accuracy dropped from 0.892 to 0.888. Though all varieties have surpassed the baseline values but there is small fall in the Ear mIoU of Apogee from 0.768 to 0.761 in comparison to the baseline CE loss.

4 DISCUSSION

In this research study, we have observed noteworthy enhancements in segmentation accuracy and mIoU following specific adjustments to parameters α and β across different wheat cultivars datasets. These improvements strengthen our hypothesis that uncertainty and feature based loss with fine tuning of α and β can enhance model performance, illustrating a complex interplay between model robustness and data specificity. Particularly, the difference in magnitude of performance across datasets underscores the influence of dataset-specific characteristics on model efficacy, challenging the viability of a uniform parameter-tuning approach across different scenarios.

Limitations: The suggested approach might not be as effective for different crops that exhibit varying structures and densities. Furthermore, there is a risk that elevated values of α and β could lead to overfitting, compromising the model's generalization across diverse agricultural scenarios. The generalizabiltity of this approach needs to be yet explored with different plant and crop species. Moreover, we rely only on ear count as sole feature in this study. We can consider different features i.e. ear ratio, ear height, ear weight so they can also contribute to better learning.

5 CONCLUSIONS

In conclusion, our study has demonstrated that uncertainty and features scores are contributing with the fine tuning of parameters α and β in our UFL framework that show notable performance enhancement of segmentation tasks with different wheat varieties. We have discerned marked improvements in segmentation accuracy and mIoU, which underscores the potential of our proposed technique. The results exhibit that a uniform parameter setting might be less effective across diverse crop species and the parameters tuning needs to be adjusted on specific data characteristics can lead to substantial improvements. This not only highlights the adaptability of our model but also points to the importance of dataset-specific strategies in agricultural applications. With the precise consideration of α and β the risk of overfitting can also be mitigated. This paves the way for more robust, accurate, and efficient models that can be pivotal in advancing precision agriculture.

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