Unbalanced datasets management for the problem of segmentation of satellite images

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***Abstract*—Unbalanced datasets pose significant challenges in the segmentation of satellite images for crop classification tasks. This paper proposes a method to mitigate the bias of models trained on such datasets without the need for additional data collection. The approach involves using spatial weight masks to modify the loss function during model training, assigning higher or lower importance to pixels based on their reliability. The reliability of pixels is determined using algorithms like K-Nearest Neighbors (KNN), and the weight masks undergo various transformations, including morphological operations and Gaussian blur, to refine their texture and ensure smoother transitions between weight factors. Experiments conducted on a dataset of satellite imagery from the Kyiv region demonstrate notable improvements in overall accuracy and Intersection over Union (IoU) when using weight masks that favor normal pixels and apply morphological dilation and Gaussian blur. The proposed method proves particularly beneficial for underrepresented crop types. Additionally, the paper explores the incorporation of synthetic data generated by a Generative Adversarial Network (GAN) alongside real data, revealing slight improvements in recognizing less common crops. Comparative analysis shows that using weight masks offers similar accuracy gains to GAN-based augmentation while being more cost-effective by eliminating the need for training an intermediary model and generating additional data. The results suggest that the proposed method of using spatial weight masks is a viable and efficient approach to managing unbalanced datasets in satellite image segmentation for crop classification tasks.**

Keywords*— KNN, Dataset Quality Assessment, Imbalanced Datasets, Hard Cases, Crop Classification, Generative Adversarial Networks, Training Data Generation, Data Set Imbalance, U- Net

I. Introduction

There are many factors that affect the quality of a machine learning model. Among the main ones, the type and architecture of the model, the learning algorithm, as well as the quantity and quality of data from the training sample can be highlighted. To some extent, the shortcomings of one component can be compensated for by improving another component, for example by increasing the dataset or using a more complex model [1] . A frequent disadvantage of the training dataset in the task of classification or segmentation is its imbalance: there is a certain subset of classes that contain few instances of data compared to other classes [2] . When training a model on such data, it tends to recognize the most represented classes well and have lower metrics on small classes. Since the least represented classes usually make up a small part of the dataset, this has little effect on the overall metrics and you can notice this problem by calculating the metrics separately for each class.

There are many problems where obtaining new data is extremely difficult, limited by the budget, or completely impossible, which excludes the solution of the given situation by expanding the dataset with instances of small classes. This problem is especially acute in the field of recognition of satellite images, where the number of images and their quality are limited by the mode of movement of satellites, time of day, weather conditions, artifacts of camera operation, etc.

This paper considers the task of segmentation of satellite images for the selection of fields with agricultural structures. With an unbalanced dataset, the model trained on it can systematically err on small fields with rare crops. To all the previous limitations of the dataset collection, the unbalanced structure of crops is added: representatives of one culture can be sown much less than others, so the imbalance of training data is a completely natural and inevitable phenomenon.

A method is proposed that allows to reduce the bias of the model, without collecting additional training data. Its purpose is to try to compensate for the lack of some dataset with a more advanced model training algorithm, the use of weight masks with modified loss functions, generative adversarial neural networks, and a combination of these two approaches are considered.

II. Related Works

To combat the problematic imbalance of classes in the dataset , various approaches and algorithms are used [2, 3] . One of them is the correction of the training package selection process, usually with the aim of equalizing the proportion of classes in it or excluding anomalous instances of data [4] . Equalization of the proportions of classes can occur at the expense of small classes, namely by artificially duplicating the data of the least represented classes, generating artificial instances of such classes and including them in the original dataset, changing the classes of specially selected data instances, or arbitrary combinations of the listed methods. Alignment can also occur due to the most represented classes, by removing part of its instances from the dataset [5] . In the first approach, data can be distorted, and the second approach can lead to information loss.

Other methods for classifying unbalanced data are the adaptation of machine learning models, the use of various data augmentation techniques , and the introduction of special metrics and/or loss functions [2, 3] . Creation of ensembles is proposed in works [6–8] , it is also proposed to have different models for different subspaces in the feature space, and a general classification model that will determine membership in one or another space [9] .

Custom designed loss functions can significantly improve the performance of models on unbalanced data, but a similar result can be achieved using modifications of standard functions using weighting factors [10, 11] . More represented classes are assigned smaller weights, and classes with a relatively small number of instances are assigned larger weights. This prompts the model to primarily study small classes. The advantages of this approach include preservation of the dataset in its original form without distortions and the absence of the need to change the learning process of the model and its architecture.

At work [12] suggests using different values of weighting coefficients for different classes and dynamically changing them in the learning process according to the current metrics. Thanks to this, the need to select weighting coefficients that would be relevant throughout the entire training period of the model disappears.

Expansion of the dataset using augmentation methods also increases the number of instances of small classes. One of the newest approaches in this area is the use of generative adversarial networks to generate artificial instances of data [13] . Generative networks are able to create high-quality multichannel images, and their spectral characteristics correspond to real images [14] .

When considering the task of segmentation of satellite images, it is appropriate to mention generative networks performing conditional generation [15] . Such models are able to generate a multi-channel image based on a given segmentation mask, which allows creating an image with the desired configuration of fields and other objects.

Work [16] is devoted to the problem of class imbalance in the problem of segmentation of satellite images and suggests using the generated images to generate classes that are not well represented in the dataset . A similar approach is demonstrated in the work [17] , where for less represented classes, more data instances were generated, and for more common classes, the number of generated data instances was lower, which generally balanced the dataset .

Numerous studies of the problem of unbalanced classes in training datasets demonstrate its relevance and the need to develop new methods and approaches.

III. Data and Method

A. Data

Four-channel satellite images of the Kyiv region from Sentinel-2 with a resolution of 10 meters were used for the experiments. To reduce the effects of cloudiness and other random interference, a satellite composite was created from images from July 2021. The resulting composite was divided into fragments of 256×256 pixels each. Taking into account the presence of 4 channels, each fragment has dimensions of 256×256×4.

The classification map developed by the Institute of Space Research of the National Academy of Sciences of the National Academy of Sciences and the Ukrainian Academy of Sciences was used as the true values of the classes [19] . The original map has 19 classes, but in this experiment the number of classes was reduced to 16 by combining some cultures with the "Other Cultures" class.

From the entire set of fragments, 4,250 instances were selected, which contained a significant proportion of pixels corresponding to agricultural crops. The resulting set was divided into training and test samples, the size of which is 2,125 fragments each. An example of visualization of the first three channels of a fragment and the corresponding segmentation mask is shown in Figure 1.

B. Determining of Ambiguous Data Instances

Generating weight masks involves using algorithms to assess pixel importance for segmentation accuracy. One method, as mentioned in [18], applies a nearest neighbor technique with variable neighbors to evaluate data instance classification reliability. Instances surrounded by same-class data are likely to be accurately classified, while those near different-class data pose challenges due to indistinguishable characteristics. These ambiguous instances can hinder model learning, making weight masks essential for accounting for such complexities during training. Although this algorithm was employed in our experiments, it's important to note that any algorithm capable of assigning reliability scores to data instances could be used for this purpose.

C. Method

In our study, we suggest applying spatial weights to the loss function calculation, associating each 4-channel composite fragment with a specific classification mask derived from its pixel values. These masks adjust the training of deep learning models by altering the loss function, traditionally represented as:

$$Loss = F\left(\hat{Y}, \hat{Y}'\right)$$

where $\hat{Y}, \hat{Y}'$ are the true segmentation mask and the model-generated mask, respectively.

Our approach modifies this to include a weight mask $\widehat{M}$ for each pixel, leading to

$$Loss = F\left(\hat{Y}, \hat{Y}', \widehat{M}\right).$$

This method differs from others that incorporate weight coefficients into the loss function. Unlike class-specific weights, our method's weights are independent of the pixel's true class. It also offers finer granularity than methods applying a single weight per dataset slice, providing a unique weight for every pixel in each slice, effectively treating the set of weighted pixels as a separate image or mask.

D. Weight Masks Generation

The experiment's test set comprises 2125 segments, each 256x256 pixels, totaling nearly 140 million pixels with about 41.89% being agricultural crops. Given this scale, the original algorithm for identifying ambiguous data instances proved inefficient. Using a KD tree reduced the per-pixel processing time but still resulted in lengthy execution times, compounded by the dense feature space which could affect parameter selection and algorithm outcomes.

To manage this, ambiguous data identification was conducted on a smaller dataset of 218,000 pixels, derived by randomly selecting up to 25,000 pixels per crop type. This subset, lacking spatial connection, allowed for a quicker determination of data reliability using the KD tree method.

For the full dataset, a KD tree built from the reduced set identified unreliable data by association. Pixels outside the agricultural crop category were deemed reliable to avoid skewing the learning process and crop classification accuracy. Future steps could involve more sophisticated methods for assigning reliability.

This process enabled the creation of masks for each dataset fragment, where reliable pixels could be emphasized in the loss function calculation to potentially enhance model stability, or alternatively, focus could be shifted to unreliable pixels to possibly improve spatial information utilization. Examples of these masks are illustrated in Figure 1.

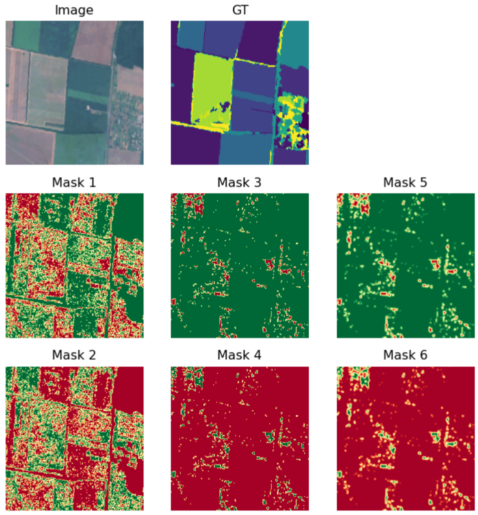

Fig. 1. Examples of satellite imagery (Image), its true segmentation mask (GT), weight masks from various sets (Mask N), the number corresponds to the set number. Masks are visualized in the RdYlGn color palette, where green represents lower values, and red indicates higher values.

The masks underwent modification through Gaussian blurring and morphological processes, specifically Erosion and Dilation. These adjustments aimed to eliminate isolated pixels and refine the mask's overall texture, ensuring a more gradual transition between weight factors. Following these transformations, the masks were normalized to ensure their coefficient averages equaled one. Six distinct mask sets were produced, with each set's parameters detailed in Table 1, and mask examples illustrated in Figure 1.

TABLE I. LIST OF TRANSFORMATIONS APPLIED TO DIFFERENT SETS OF WEIGHT MASKS

#	The name of the set	Focus of weighting factors	Morphological transformations	Gaussian blur
1	Normal focus	normal pixels (4:1)	-	-
2	Hardcase focus	ambiguous pixels (4:1)	-	-
3	Normal focus Dilation	normal pixels (4:1)	Dilation (3×3)	-
4	Hardcase focus Erosion	ambiguous pixels (4:1)	Erosion (3×3)	-
5	Normal focus Dilation Gauss	normal pixels (4:1)	Dilation (3×3)	5×5
6	Hardcase focus Erosion Gauss	ambiguous pixels (4:1)	Erosion (3×3)	5×5

E. Training the Generative Model

The generative model, aimed at mitigating class imbalance, creates an expanded dataset for training the segmentation model, incorporating weight masks during its training phase [17]. The model, based on U-Net architecture [20], produces two outputs: one for generating images closely resembling real ones, using mean square error (MSE) as its loss function, and the other for binary cross-entropy (BCE). The overall loss is a combination of these:

$$Loss = MSE\left(\hat{R},\hat{G}\right) + \alpha BCE\left(\hat{Y},\hat{Y}'\right)$$

$$MSE\left(\hat{R},\hat{G}\right) = \frac{1}{n}\sum_{i,j,k}\left(R_{ijk} - G_{ijk}\right)^2$$

$$BCE\left(\hat{y},\hat{y}'\right) = \frac{-1}{m}\sum_{i,j}\sum_{k=1}^{C} y_{ijk}\log\left(y_{iik}'\right)$$

where α the balancing coefficient, was set to 0.01 for this experiment, n is the number of pixels in the image multiplied by the number of channels, $\hat{R},\hat{G}$ is the real and generated image, $\hat{y}',\hat{y}$ is the response of the discriminator and true values similar in dimensions, m is the number of pixels in them, C is the number of classes.

F. Training the Segmentation Model

Each fragment's weight mask is incorporated into the loss function calculation by the segmentation model, which utilizes the U-Net architecture. The model processes data batches of size N×256×256×4, with 'N' representing the batch size, '256×256' the fragment dimensions, and '4' the channel count. It produces a single output with dimensions N×256×256×16, where '16' corresponds to the class count.

For a single training step without segmentation masks, data of size N×256×256×4 is input into the model, producing an output of N×256×256×16, which is then compared to the actual labels of size N×256×256 using cross-entropy loss:

$$BCE\left(\hat{Y},\hat{Y}'\right) = \frac{-1}{n}\sum_{i,j}\sum_{k=1}^{C} Y_{ijk}\log\left(Y_{iik}'\right)$$

where $\hat{Y},\hat{Y}'$ are the true and predicted masks, n is the pixel count per fragment.

To incorporate spatial weight masks, the same process is followed, but with weight masks of size N×256×256 added. The modified loss function, integrating mask values as weights, becomes:

$$BCE\left(\hat{Y},\hat{Y}',\hat{M}\right) = \frac{-1}{n}\sum_{i,j} M_{ij}\sum_{k=1}^{C} Y_{ijk}\log\left(Y_{iik}'\right)$$

This approach adjusts each pixel's impact on the loss and model parameter gradients, giving more significance to pixels with higher weight mask values.

Experiments to fine-tune spatial weight masks used different masks and real data, with additional trials incorporating both real data with masks and generated data without masks from generative models. Ultimately, after optimizing mask parameters for both generation and segmentation, various mask combinations for each task were evaluated.

IV. EXPERIMENTAL RESULTS

Fourteen segmentation models were developed, with seven utilizing only authentic imagery and the remainder incorporating both real and synthesized images. Within each group, one model served as a control, trained without weight masks, while the others were enhanced with weight masks detailed in Table 1.

For the real-data-only models, performance metrics like precision, recall, and IoU were assessed. A select few outperformed the control model, with the top two featured in Table 2. It presents the accuracy (P), recall (R), and Intersection over Union (IoU) for models trained exclusively with real data and weight masks, in comparison to the baseline model. The model names correlate with the specific mask sets utilized during training. AAC represents the average metric scores, while OA denotes the overall accuracy and IoU. These successful models prioritized normal over unreliable pixels through higher weight coefficients and employed a 3×3 kernel for white stretching to minimize edge anomalies. Additionally, a 5×5 kernel Gaussian blur was applied to their masks, improving performance particularly for underrepresented crops like sugar beet and soybean. The adjustments led to a notable increase in overall metrics, with accuracy and IoU rising to about 78.7% and 66.3% from baseline values of 77.7% and 64.1%, respectively.

TABLE II. PEROFMANCE METRICS FOR MODELS TRAINED WITH REAL DATA

Crop Class Name	Baseline Model			Normal focus Dilation			Normal focus Dilation Gauss		
	R (%)	P (%)	IoU	R (%)	P (%)	IoU	R (%)	P (%)	IoU
Wheat	83.5	71.5	62.7	**86.6**	71.8	**64.6**	84.2	**72.4**	63.8
Rapeseed	**29.3**	37.7	**19.7**	3.1	42.9	3.0	17.8	**49.5**	15.1
Maize	**89.9**	83.8	76.6	89.5	87.6	**79.5**	89.2	**87.8**	79.4
Sugar beet	0.0	0.0	0.0	**52.0**	54.5	**36.3**	31.7	**62.1**	26.6
Sunflower	92.7	80.5	75.7	89.7	**86.3**	**78.5**	**92.8**	82.3	77.4
Soybeans	54.9	80.8	48.6	62.4	**81.3**	54.6	**66.0**	78.4	**55.8**
Other crops	3.2	26.6	2.9	**7.4**	33.2	**6.5**	**7.4**	**35.8**	**6.5**
Barley	22.4	45.8	17.7	22.9	**50.2**	18.7	**26.6**	45.9	**20.3**
Peas	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
AAC (%)	41.8	47.4	33.8	46.0	56.4	38.0	**46.2**	**57.1**	**38.3**
OA (%)	77.3		64.1	**78.7**		**66.3**	78.6		66.2

Among the models trained with both real and synthesized data while incorporating weight masks, only one demonstrated marginal metric enhancements over the baseline model, which was similarly trained but without masks. This model's weight masks favored unreliable pixels with higher coefficients, and underwent both a narrowing process via a 3x3 kernel and smoothing with a 5x5 Gaussian blur. Additionally, a separate test was carried out where weight masks were applied in the training of the generative model but omitted in the segmentation model's training. Table 3 displays the accuracy (P), recall (R), and Intersection over Union (IoU) for models trained with both real and synthetic data using weight masks, alongside comparisons to the baseline model. Model names reflect the mask sets employed during their training. "NW" indicates that no weight masks were utilized in the segmentation model's training phase. While overall metrics remained unchanged, there was a slight improvement in the recognition of less common crops.

TABLE III. PEROFMANCE METRICS FOR MODELS TRAINED WITH MIXED DATA

Crop Class Name	Baseline Model GAN			Hardcase focus Erosion Gauss			Hardcase focus Erosion Gauss NW		
	R (%)	P (%)	IoU	R (%)	P (%)	IoU	R (%)	P (%)	IoU
Wheat	**85.8**	73.2	**65.3**	84.3	**73.5**	64.6	84.6	72.8	64.3
Rapeseed	37.1	**52.0**	27.6	42.3	46.3	**28.4**	**43.0**	44.8	28.1
Maize	88.2	87.6	78.4	87.8	**88.1**	78.5	**88.4**	87.8	**78.7**
Sugar beet	15.4	**65.8**	14.3	**46.1**	51.4	32.1	43.7	56.3	**32.6**
Sunflower	**92.9**	82.8	**77.9**	90.5	**84.5**	77.6	91.8	83.4	77.6
Soybeans	68.2	73.1	54.5	66.1	**75.6**	54.5	**68.7**	74.1	**55.4**
Other crops	**9.7**	33.2	**8.1**	7.8	34.9	6.8	4.5	**35.5**	4.2
Barley	**30.0**	48.2	**22.7**	26.0	**50.5**	20.7	20.2	46.3	16.4
Peas	**0.1**	**5.6**	**0.1**	0.0	2.8	0.0	0.0	1.7	0.0
AAC (%)	47.5	57.9	38.8	50.1	56.4	40.3	**58.3**	**61.7**	**46.8**
OA (%)	**78.6**		**66.2**	**78.6**		**66.2**	**78.6**		66.1

Figure 2 illustrates segmentation results on a real image slice from the test dataset using the aforementioned models. Models employing masks exhibit fewer visual artifacts. Overall, generative models benefit most from weight masks that assign higher coefficients to unreliable pixels. Conversely, segmentation models perform better with masks that favor normal pixels with larger weights. In both scenarios, minimizing the boundary between unreliable and reliable pixels through morphological operations is crucial. The use of Gaussian blur on masks is conditional; it may enhance outcomes or have no significant impact.

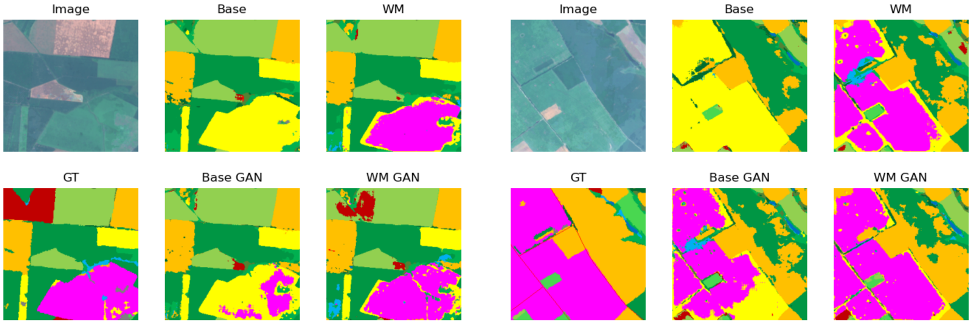

Fig. 2. Visualization of satellite imagery (Image), true segmentation masks (GT), results of base models (Base, Base GAN), and results of models using weight masks (WM, WM GAN).

Comparing the performance metrics of models trained with synthetic images to those trained on real data with weight masks reveals an interesting dynamic. In certain aspects, the GAN-trained model outperforms the mask-utilizing model and vice versa. While the accuracy gains between the two approaches are similar, using weight masks offers a cost-effective advantage by eliminating the need for training an intermediary model and generating additional data, making it a more efficient alternative to GAN-based augmentation.

V. Conclusions

This paper investigated methods for managing unbalanced datasets in the problem of satellite image segmentation for crop classification. The proposed approach involves using spatial weight masks to modify the loss function during model training. These weight masks assign higher or lower importance to pixels based on their reliability, as determined by algorithms like KNN. The masks underwent various transformations, including morphological operations and Gaussian blur, to refine their texture and ensure smoother transitions between weight factors.

Experiments were conducted using a dataset of satellite imagery from the Kyiv region. Models trained with weight masks favoring normal pixels and applying morphological dilation and Gaussian blur showed notable improvements in overall accuracy and IoU compared to the baseline. The use of weight masks proved particularly beneficial for underrepresented crop types like sugar beet and soybean.

Additional experiments incorporated synthetic data generated by a GAN model alongside the real data. While the inclusion of synthetic data led to slight improvements in recognizing less common crops, the overall metrics remained similar to the baseline. Interestingly, applying weight masks during the GAN training phase but omitting them during segmentation model training yielded marginally better results for rare crop types.

Comparing the performance of models trained with synthetic data to those trained on real data with weight masks revealed that both approaches offer similar accuracy gains. However, using weight masks eliminates the need for training an intermediary model and generating additional data, making it a more cost-effective alternative to GAN-based augmentation.

In conclusion, the proposed method of using spatial weight masks to manage unbalanced datasets in satellite image segmentation has shown promising results. By assigning higher importance to reliable pixels and applying appropriate mask transformations, the models achieved improved accuracy and IoU, especially for underrepresented crop classes. This approach offers a viable and efficient alternative to data augmentation techniques like GAN-based synthetic data generation. Future research could explore more sophisticated methods for assigning pixel reliability and investigate the optimal combination of mask transformations for specific datasets and segmentation tasks. Additionally, the utilization of time series satellite data instead of single images could potentially increase the accuracy of classification by leveraging temporal patterns. By incorporating multi-temporal information, the models can capture the dynamic changes in crop growth and phenology, which can provide valuable discriminative features for improved classification performance. This approach could be particularly beneficial for distinguishing crops with similar spectral characteristics but different growth cycles. Integrating time series data with the proposed spatial weight mask method could further enhance the management of unbalanced datasets and improve the overall accuracy of satellite image segmentation for crop classification tasks.

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