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Crop Classification using Semi supervised Learning on Data Fusion of SAR and Optical Sensor

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Abstract

Crop maps are essential tools for creating crop inventories, forecasting yields, and guiding the use of efficient farm management techniques. These maps must be created at highly exact scales, necessitating difficult, costly, and time-consuming fieldwork. Deep learning algorithms have now significantly enhanced outcomes when using data in the geographical and temporal dimensions, which are essential for agricultural research. The simultaneous availability of Sentinel-1 (synthetic aperture radar) and Sentinel-2 (optical) data provides an excellent chance to combine them. Sentinel 1 and Sentinel 2 data sets were collected for the Cape Town, South Africa, region. With the use of these datasets, we use the fusion technique, particularly the layer-level fusion strategy, one of the three fusion procedures (input level, layer level, and decision level). Also, we will compare the results before and after the fusion and discuss the recommended method for converting from a multilayer perceptron decoder to a semi-supervised decoder architecture. The total testing accuracy produced by the Ada-Match semi-supervised decoder approach was 80.3%. We conduct studies to demonstrate that our methodology not only outperforms prior state-of-the-art approaches in terms of precision but also significantly decreases processing time and memory requirements.

1. Introduction

For efficient agricultural monitoring, accurate crop maps must be created during the current growing season. Large-scale studies on regional crop distribution from year to year have been done by a number of organisations, but little is known about the dynamics of crop composition and geographic range within a season. Understanding how crops are dispersed throughout the early phases of development enables timely modification of crop planting structure, agricultural management, and decision-making. Machine learning techniques may be used in a wide range of high-impact applications as more public and commercial entities have access to high-quality satellite data. One of these is the classification of crop varieties, which presents a significant challenge to those in charge of agricultural and environmental policies. According to Foerster et al. (Foerster et al.), crop type prediction is useful for managing the food supply and children's wellness in underdeveloped nations, as well as for simulating flood damage assessment and water quality. Despite the fact that crop maps are only useful during the growing season when used as input for crop area projections, hazard prediction, or water consumption calculations, there has recently been an increase in the demand for information on the geographic distribution and dynamics of various crop types. Yet, it can be difficult to accurately determine crop dispersion, especially early in the growing season.

One of the most important ecosystems for human subsistence is agriculture. Due to the population's rapid expansion, bad farming techniques, a rise in pest damage brought on by climate change, the loss of fertile land due to human activities like urbanisation, and inadequate pest control, agricultural resources are under significant supply-side stress. We have developed a deep learning architecture that appropriately categorises the crop types in each agricultural area to address this issue. The Sentinel 1 and 2 (Stendardi et al. Wang et al.) crop groups have labels for barley, canola, lucerne/medics, wheat, and small grain grazing. To create a model that would offer a rapid and accurate approach to categorising the crop varieties in croplands, we wish to employ deep learning techniques. With this approach, which also evaluates the danger of drought, farmers can forecast crop yields on diverse land patterns.

Its simultaneous availability provides a tremendous chance to integrate Sentinel-1 (synthetic aperture radar) and Sentinel-2 (optical) data. To precisely address the operational requirements of the Copernicus program, the European Space Agency (ESA) has created a new family of missions dubbed Sentinels. Each Sentinel mission is made up of a constellation of satellites that both meets the requirements for revisit and coverage and supplies reliable data for the Copernicus services. These trips contain a variety of technical gear, including radar and multi-spectral imaging equipment for monitoring the surface of the earth, the oceans, and the atmosphere.

Radiant ML Hub, an open-source repository for machine learning datasets, provided the training and testing data sets for Sentinel 1 and Sentinel 2. The obtained datasets were meticulously inspected, validated, and normalised in order to remove the datasets' noise. A vegetative index (VI) is a spectral imaging modification of two or more picture bands (Lymburner). There are several VIs, many of which act in the same way. A number of the indices use the inverse connection between red and near-infrared reflectance, which is connected to healthy green vegetation.

To effectively categorise and anticipate the crop type, this work combines semi-supervised learning algorithms with deep learning methods like pixel setting and temporal attention encoder architecture. This method, as opposed to post-season crop mapping, offers the benefit of mapping in-season crop types throughout crop growth to improve agricultural production management. Crop mapping (Nijhawan et al.) based on high-resolution satellite data may address a wide range of relevant issues, including crop area estimation, yield forecasts, and drought risk assessment.

2. Study Area and Datasets

Radiant ML Hub, an open-source repository for machine learning datasets, provided the training and testing data sets for Sentinel 1 and Sentinel 2. The Sentinels mission family is being developed by the European Space Agency (ESA) primarily to meet the operational requirements of the Copernicus program. The Radiant Earth Foundation makes vector data with restricted dissemination rights accessible to the Western Cape Department of Agriculture (WCDOA). Each Sentinel mission is made up of a constellation of satellites that both meets the requirements for revisit and coverage and supplies reliable data for the Copernicus services. Sentinel-1 is an all-weather, day-and-night, polar-orbiting radar imaging mission that monitors both the land and the water. On April 3, 2014, Sentinel-1A was launched, and on April 25, 2016, Sentinel-1B A Soyuz rocket launched from the European Spaceport in French Guiana carried both into orbit. Sentinel-1B's mission was finished in 2022, and Sentinel-1C will launch as soon as it is feasible to do so. Sentinel-2 is a polar-orbiting, multispectral, high-resolution imaging mission that keeps an eye on the landscape. It might show pictures of things like vegetation, soil and water cover, interior rivers, and coastal areas. Information for emergency services may also be supplied via Sentinel-2. Launch dates for Sentinel-2A and Sentinel-2B are June 23, 2015, and March 7, 2017, respectively.

The dataset was obtained from the source in an adjusted and normalised manner. To put pixel values into a single scale while keeping underlying similarities and differences, the various bands are individually normalised (per picture, date, and channel). In addition to feature values, these sensors also preserve the dates on which each box was purchased. While the acquisition dates for Sentinel-1 are predetermined, those for Sentinel-2 are subject to change because of the cloud reduction method that is being implemented. Time Series x Number of Channels x Number of Pixels in a Parcel is the format used to store all parcels (npz format). This method is known to give larger dynamic range characteristics less weight, and machine learning algorithms are known to converge more quickly. A detailed analysis and visualisation were done on the dataset. Between May 2017 and March 2018, aerial and ground surveys were used to collect crop data for the dataset. Its simultaneous availability provides a tremendous chance to integrate Sentinel-1 (synthetic aperture radar) and Sentinel-2 (optical) data. The fusion strategy was applied using these datasets.

TABLE 1. Data Properties

Property Name	Description	Parameters
crop_id	Crop Class	1, 2, 3, 4, 5
crop_name	Crop Type	Wheat, Barely, Canola, Lucerne, Small grain grazing
fid	Field ID	Integer

The datasets for the two training areas and one testing region are shown in the images below. 1715 parcels make up the first training zone, 2436 parcels make up the second, and 2417 parcels make up the testing region.

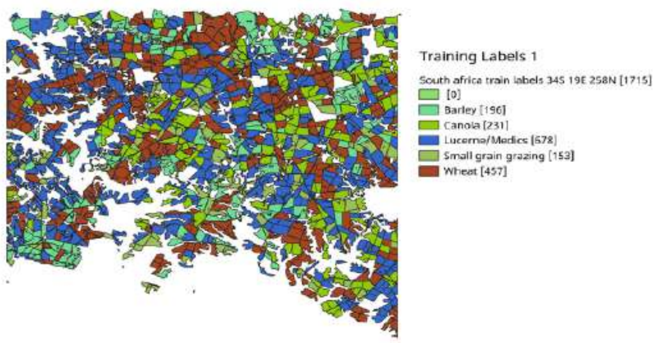

FIGURE 1. Training Area - 1

The datasets were also shown for the 34S, 19E, 258N, and 34S, 259N locations in Cape Town, South

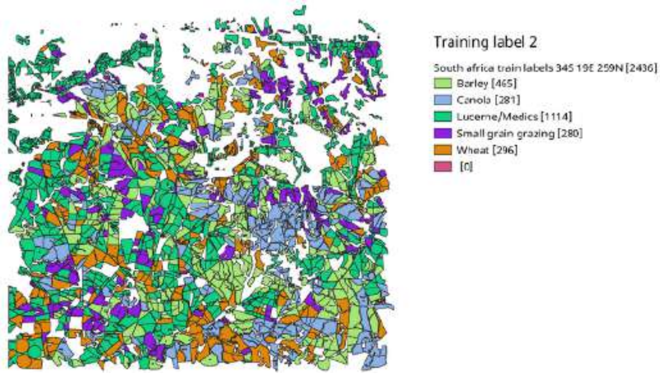

FIGURE 2. Training Area - 2

Africa, using the Python matplotlib module. The 5-day timeseries plot for the Sentinel 1 and Sentinel 2 datasets was significantly influenced by the vegetative index. This collection comprises images of an area in South Africa's Western Cape taken by many satellites using multispectral and synthetic aperture radar (SAR) (Adeli et al. Chang-An et al.) as well as ground-based crop type labels. Five distinct types of crops were grown in 2017: lucerne/Medics, canola, wheat, barely, and small grain grazing. The AOI is made up of three tiles. Two tiles are provided as training labels, and one tile will be used to test the dataset. The input photos are time series (daily and 5-day composite) data from Sentinel-2 and Sentinel-1. There is a separate collection for each source. Also shown here are the five-day time series plots for the training regions, Sentinel 1 and Sentinel 2, respectively.

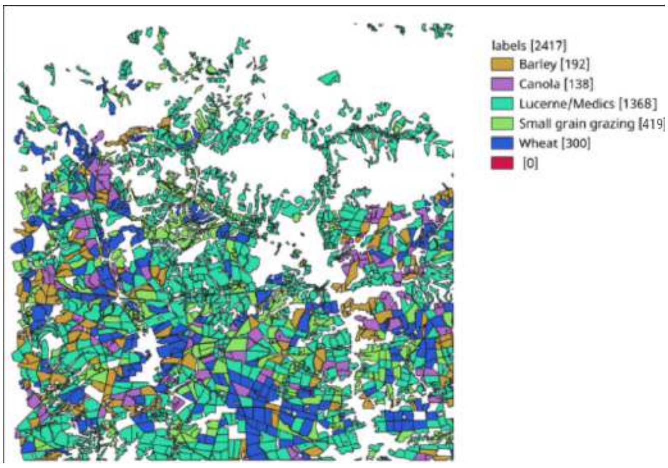

FIGURE 3. Testing Area

3. Methodology

The first inputs of the PSE-TAE encoder architecture are the Sentinel-1 and Sentinel-2 data sets (Fare

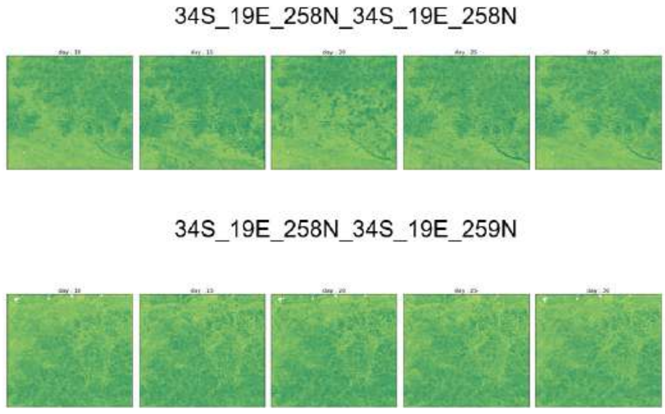

FIGURE 4. **Sentinel 1 Five days time series plot**

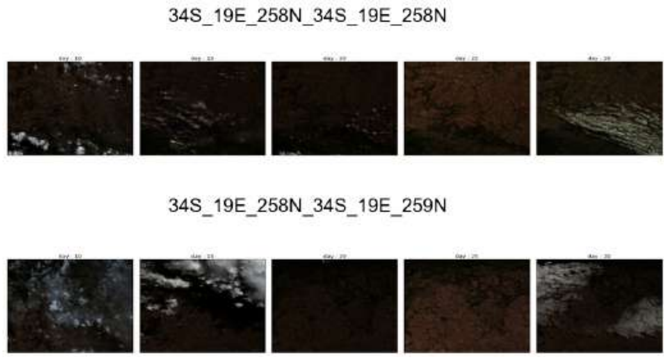

FIGURE 5. **Sentinel 2 Five days time series plot**

et al.). We choose the Pixel Set Encoder-Temporal Attention Encoder (PSE-TAE) over other supervised learning algorithms specifically designed for SITS classification as the deep learning architecture for studying various fusion methods (Yuan et al.). The PSE-TAE architecture is a spatio-temporal classifier for object-level SITS classification. We assume that most European disciplines have access to and are familiar with geometry. Three factors led to the choice of PSE-TAE: I) It manages different parcel sizes and allows irregular time sampling. II) Formation of long-term relationships through the process of self-awareness (Vaswani et al.). III) Operations with reduced memory footprint are more computationally efficient. The two main components of the system are the spatial coder (pixel set coder) and the temporal attention coder. In this case, layer-level fusion is also performed after the PSE module using concatenation technology. The time series embedding generated by PSE is the same length as the input time series. Therefore, Sentinel-1 and Sentinel-2 embeddings can be concatenated only if their PSEs are of the same length. The input time series of Sentinel-1 is resampled using the same method used in the initial fusion to adjust the length of the output time series of Sentinel-2. It is also possible to directly rescale the Sentinel-1 PSE embedding. However, this makes her PSE module on the satellite larger than it needs to be. The classification implementation follows a semi-supervised learning (Y. C. A. P. Reddy, Pulabaigari, and B. E. Reddy) approach. This replaces the multilayer perceptron decoder (Karami, Attari, and Tavakoli) with a new semi-supervised decoder. This type of learning uses both labelled and unlabelled data to train the system. The amount of labelled data in this combination is typically quite small compared to the amount of unlabelled data. The basic process is to group related data using an unsupervised learning algorithm and then use the previously labelled data to label the remaining unlabeled data.

3.1. Pixel Set Encoder

CNNs have become the industry standard for extracting spatial information from images in recent years. Our results suggest that convolution may not be the best strategy for analysing agricultural land in medium-resolution satellite imagery. As mentioned earlier, it is difficult to obtain textural data from satellites using the default spatial resolution and high return frequencies. Second, to effectively train a CNN, the data should be organised into stacks of images of equal size (Nowakowski et al.). Due to the different packet sizes, this method consumes a lot of memory. This corresponds to repeated oversampling of large portions of small parcels to prevent loss of texture information in large parcels. To circumvent these two problems, we developed an alternative design called the DeepSet architecture (Zaheer1 et al.) and the Pixel-Set Encoder (PSE), inspired by the widely used point-set encoder PointNet for processing 3D point clouds. Suggest. Instead of using texture information, the network computes learned statistical descriptors of the spectral distribution of pixel data. The S[1-N] set of S pixels is randomly selected from the N pixels in the parcel. Each randomly selected pixel is repeated to match this given size if the total number of pixels in the image is less than S.We use the same set S to sample all T gatherings of a given parcel. A common multilayer perceptron (MLP1) is used to process each sampled pixel. A number of linearly corrected units, batch norms, and fully connected lay-

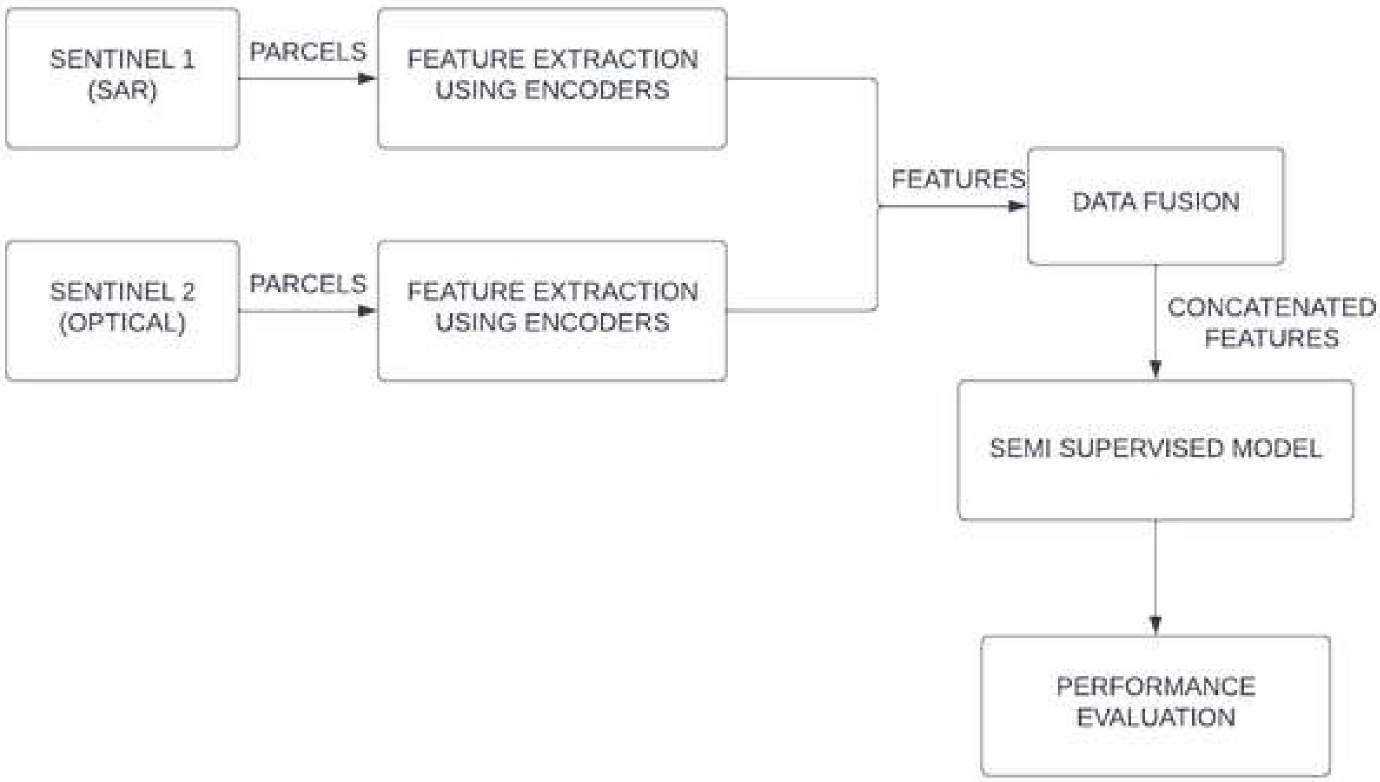

FIGURE 6. **Methodology for the training process using Semi Supervised Learning**

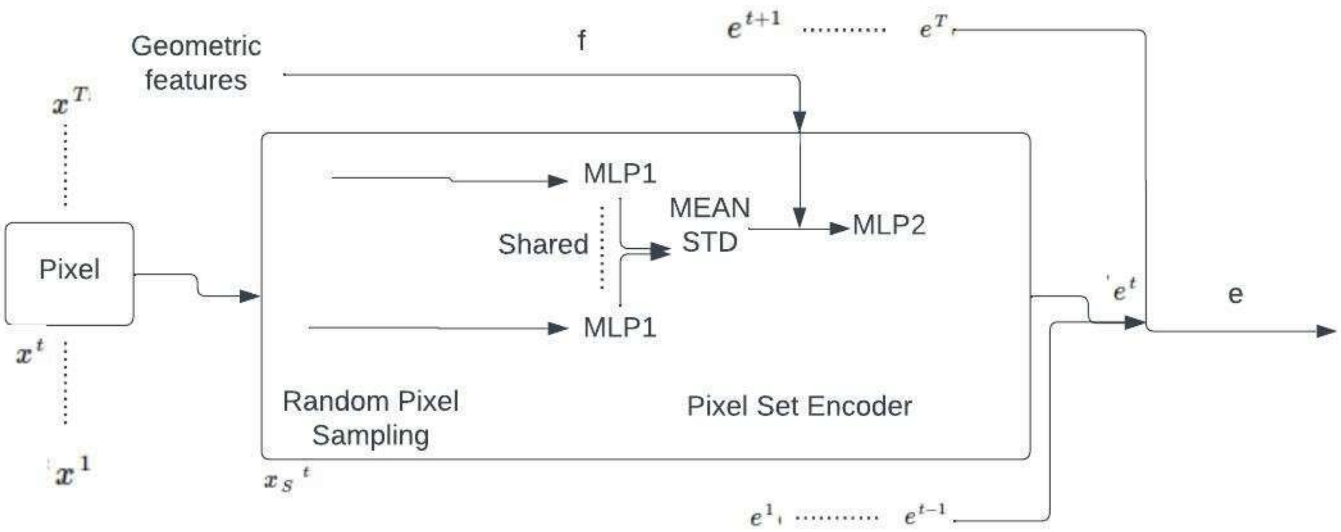

FIGURE 7. **Pixel Set Encoder**

ers make up its structure. The resulting data sets are merged along the S-dimensional pixel axis to produce a vector that contains all the statistics for the packet and is tolerant of pixel index permutation. The geometric attributes (f) that we add to this learned feature are the perimeter, the number of pixels N, the coverage factor (N divided by the number of pixels in the bounding box), and the ratio of perimeter to surface area of the parcel. This vector is used by the MLP2 perceptron to generate the spatio-spectral embedding e(t) of the parcel at time t.

3.2. Temporal Attention Encoder

Self-awareness processes form the basis of TAE. The idea of attention is one of his best known in

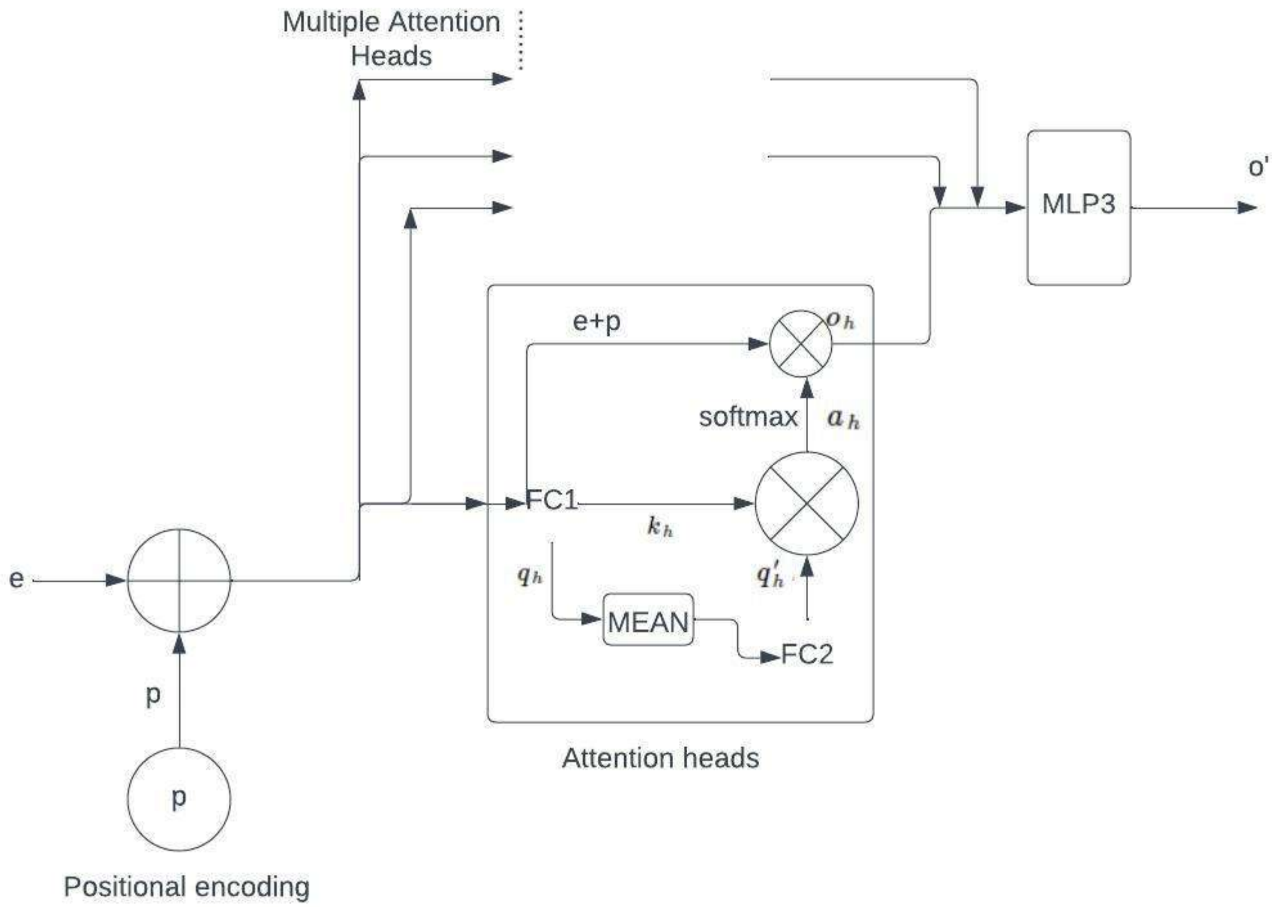

FIGURE 8. **Temporal Attention Encoder**

deep learning. The Seq2Seq seq model was used for neural machine translation as the main purpose of this technique, but has now been extended to include photo captioning (Sutskever et al.). A self-aware process is used to construct Temporal Attention Encoders (TAE) (Niu, Zhong, and Yu). In order to build a representation of the sequence, this method pays special attention to the links between different input sequence positions (time series in this case). This technique emphasises connections between multiple input sequence positions to determine the representation of the sequence, in this case the time series. Using a position encoder (based on sine and cosine functions) preserves the relative position of the sequence and adds this information to the PSE embedding. TAE immediately accepts two embeddings added together. Coming to RNNs (Sherstinsky), which process data sequentially, the application of multi-head attention allows the model to accept inputs from a large number of representational subspaces at different temporal positions while allowing computational parallelization and optimization. can be continuously paid attention to. A multi-layer perceptron (MLP) is used to analyse the generated TAE embeddings and generate class logits.

3.3. Fusion

The three basic fusion techniques (Ofori-Ampofo, Pelletier, and Lang) are input-, layer-, and decision-level fusion processes. The best fusion technique to improve the classification performance of optical radar is the layer-level fusion performed in this work. The Pixel-Set Encoder-Temporal Attention Encoder (PSE-TAE) (He, Chow, and J.-D. Zhang Fiorini, Ciavotta, and Maurino) is a state-of-the-art architecture that uses it, specifically created for object-based classification of satellite imagery time series (SITS), and is self-aware. Based on the attention process, this limitation is overcome by using

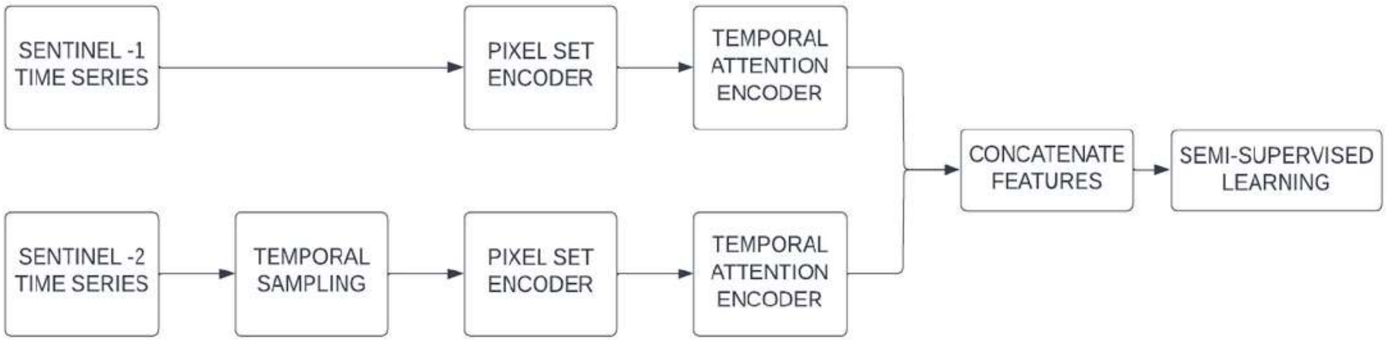

FIGURE 9. Layer level fusion architecture

a pixelset encoder in your design. These encoders use randomly selected samples of pixels to provide a learned statistical descriptor of the spectral distribution of the parcel data. Pixels are processed to construct the spatio-spectral embedding of each datum using a general continuous MLP. Attention mechanisms are another way deep neural networks can selectively focus on certain relevant information and ignore other information. TAE is based on a process of self-awareness. Layer-level fusion technology fuses data by concatenating two separate PSE-TAE network embeddings after the TAE module. The MLP classifier follows concatenation. The process is easy because both embeddings have the same size.

3.4. Fix Match Learning Algorithm

FixMatch (Sohn et al.) integrates pseudo-labelling, consistency correction and SSL (semi-supervised learning) techniques. These two components are combined, and separate weak and strong increments are used to adjust consistency, which is one of its characteristics (H. Zhang et al.). Let X = (xb, pb) be the set of examples of an L-class classification problem, denoted by B, where xb denotes the training examples and pb the features of one hot label. Let U = ub: b (1,..., B) be the set of unnamed instances of B and let B be a hyperparameter that controls the relations between X and U . Let pm(y, x) be the predicted class distribution of the model for input x. The letter H represents the cross entropy between the probability distributions of p and q (p, q). Modern state-of-the-art SSL algorithms are essential for consistency and regularity. Basing its assumptions on the idea that a model should produce results that are comparable when given transformed copies of the same image, the consistency correction utilises unlabeled data. The method, called pseudo-labeling, exploits the model's inherent ability to assign false labels to unlabeled data. This is particularly related to the use of ”hard” labels (ie, the arg-max output of the model) and limiting the use of false labels to those with the highest probability greater than a certain threshold. The FixMatch loss function consists of two entropy loss terms, called uncontrolled loss (”u”) and controlled loss ('s"), applied to labelled data. Specifically, it is essentially a cross-entropy loss that occurs in samples with weak enhanced labelling. FixMatch creates a false label for each unlabeled example, which is used for a typical cross-entropy loss. Using the equation qb = pm(y — ub), we first calculate the class distribution predicted by the model for the unlabeled image with weak enhancement .Cross-entropy loss is then applied to the model output, resulting in a greatly improved version of UB, where qb acts as a pseudo stamp.

3.4.1. Match Learning Algorithm

The Mix-Match (David et al.) method corrects each labelled data point once per set and corrects each unlabeled data point K (hyperparameter) times. For each K improved record, the model is asked to predict the L class probability, and its average is then used as the prediction for all K records. This average is modified to reduce entropy before the final prediction is made. W is created by merging and reordering enhanced labelled and unlabeled data. The amount of tagged data in the set is considered when combined with the first —X— to create the X' and W elements. The unsigned data in the array is combined with the remaining elements of W to create U . Model X's prediction should match the labelled result, while Model U's prediction should match the unlabeled estimates because lambda is 0.5 and MixUp prefers the first point over the sec-

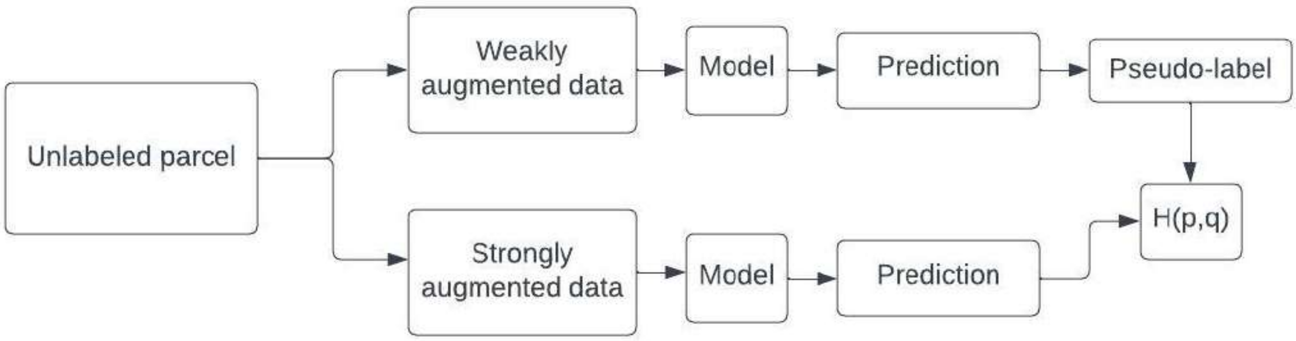

FIGURE 10. Fix Match Semi supervised algorithm

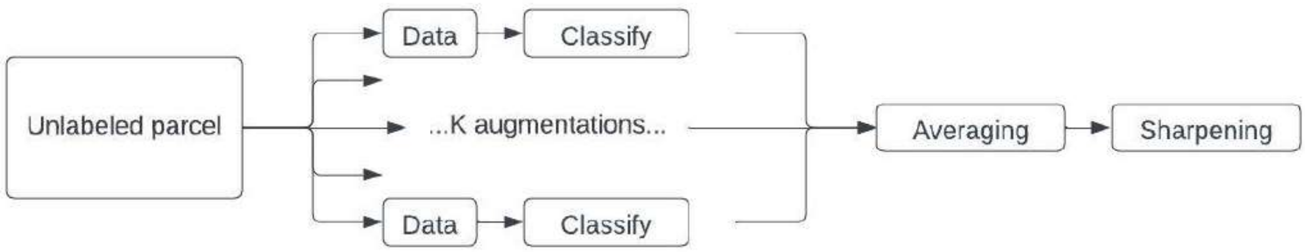

FIGURE 11. Mix Match Semi supervised algorithm

ond. Since we are aware of the exact output of the labelled data, the cross entropy loss H is a suitable loss function for Lx(a,b). The total loss is finally obtained by combining the losses with the hyperparameter lambda.

3.5. Ada Match Learning Algorithm

AdaMatch (Berthelot et al.) combines three techniques to deal with inconsistencies between the source and target distributions: random logit interpolation, a relative confidence threshold, and modified distribution alignment.

The algorithm is implemented as follows:

There were originally two augmentations—one weak and one strong—created for each input. The input is then split into two batches: one batch contains solely source input, while the other comprises both source (labelled) and target (unlabeled) data. These two batches are then processed by the model to create logits. The logits from a batch are affected by its own batch norm statistics. To accomplish consistency regularisation, the source logit and the logit obtained from the mixture are mixed using random logit interpolation.

3.5.1. Random logit interpolation:

Using random logit interpolation, the source domain's joint batch statistics are randomly added to the mixture. As a result, more typical batch statistics for both domains are produced.

3.5.2. Distributive alignment:

In real-world machine learning applications, domain shifts in the training data are a concern since they take place when the data originates from several sources. In spite of these changes, a good ML model, for instance, developed via learning a domain-invariant representation, should continue to function effectively.

The distribution of the class predictions can be more closely matched to the actual distribution by using distributive alignment. Without it, the classifier can only predict which class will be the most common or show different failure modes. If we knew the target label distribution, we would use it right away. When the destination label distribution is unknown, the only distribution that is available is the source label distribution. The class with the highest level of certainty is used to assign pseudo-

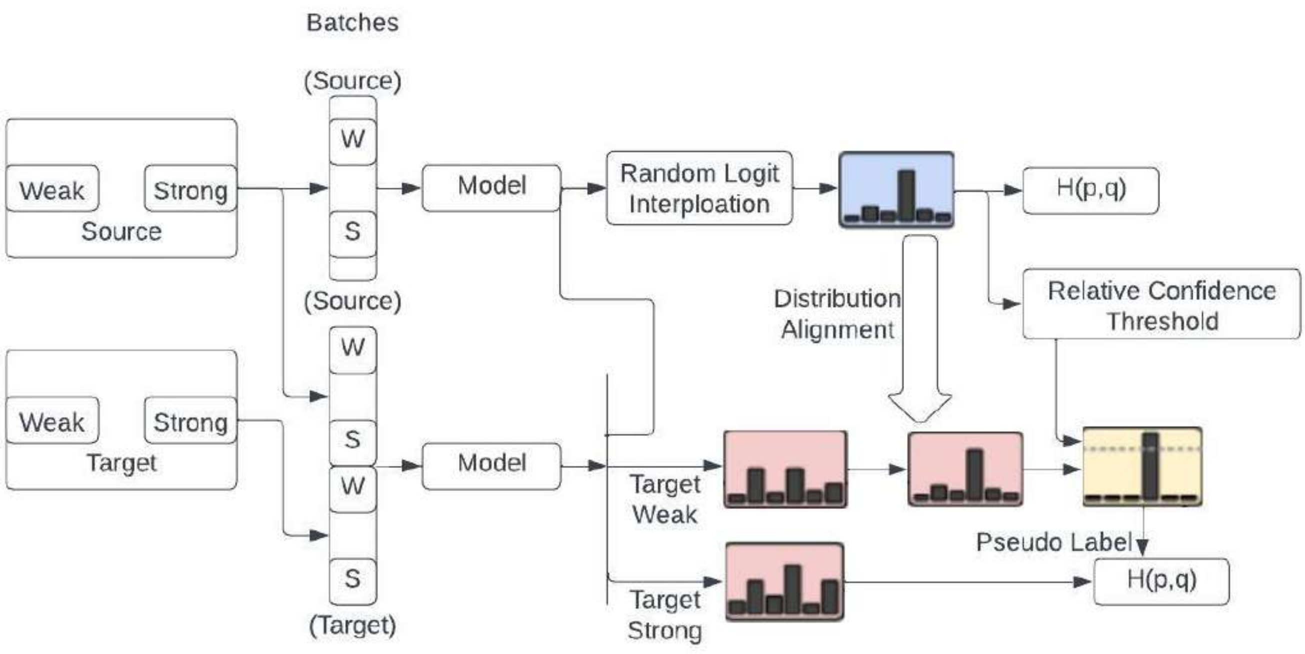

FIGURE 12. **Ada Match Semi supervised algorithm**

labels to these outputs.

3.5.3. Relative confidence threshold:

Particularly for non-distributed data, ML models are not well optimised. The relative confidence threshold is changed based on the classifier's level of trust in the weakly supplemented source data and the user-provided confidence threshold. Adamatch is preferable to fix match and mix match because it uses distributive alignment and consistency regularisation (fix match).

4. Results and Discussion

The key benefit of semi-supervised learning over the other two is that it allows us to enhance the performance and generalizability of our model. Large datasets (particularly for business reasons) could only include a few labels since labels are costly. We can work with these kinds of datasets using semi-supervised learning without having to choose between supervised learning and unsupervised learning.The Ada Match algorithm outperformed the other two semi-supervised

algorithms in terms of training validation and testing accuracy. Consequently, the semi-supervised decoder has been successfully implemented after fusion in place of the multilayer perceptron decoder. Our research demonstrates that our methodology significantly decreases processing time and memory requirements while outperforming prior state-of-the-art approaches in terms of precision. The following shows the outcomes:

The AdaMatch semi-supervised decoder's testing accuracy is presented in the table above after the various training and validation accuracy levels. The PSE-TAE (Pixel Set Encoder and Temporal Attention Encoder) and layer-level fusion designs were used. By training Sentinel 1 and Sentinel 2 individually, 66 and 67 percent accuracy for both processes were attained without the need for layer-level fusion. When layer-level fusion was used, the accuracy rose to 94 percent, and the graph shows that the accuracy increases as the number of epochs increases. Subsequently, semi-supervised decoders took the place of the traditional multi-layer perceptron decoder. We looked at and used Fix match, Mix match, and Ada match as semi-supervised decoders. The fix match algorithm obtained 93 percent training and validation accuracy, followed by mix match (94.2 percent), and Ada match (94.8 percent). Ada Match outperforms Mix Match, even if there is a little gap in the accuracy of the two approaches. Finally, the model was assessed using the testing dataset using the Pixel Set-Temporal Attention classifiers and the Ada Match semi-supervised decoder. It produced an

TABLE 2. Training-Validation and Testing Accuracies

	Sentinel 1	Sentinel 2	Data fusion (MLP decoder)	Data Fusion (Semi Supervised Decoder)			
				Fixmatch	Mixmatch	Adamatch	Testing
F1-SCORE	0.51	0.56	0.93	0.92	0.93	0.94	0.72
IOU	0.38	0.43	0.88	0.86	0.87	0.90	0.72
Overall Accuracy	0.65	0.66	0.94	0.93	0.94	0.95	0.80
Kappa Coefficient	0.51	0.52	0.92	0.91	0.92	0.93	0.70

accuracy of 80.3%. This is a diagram of the resultant confusion matrix:

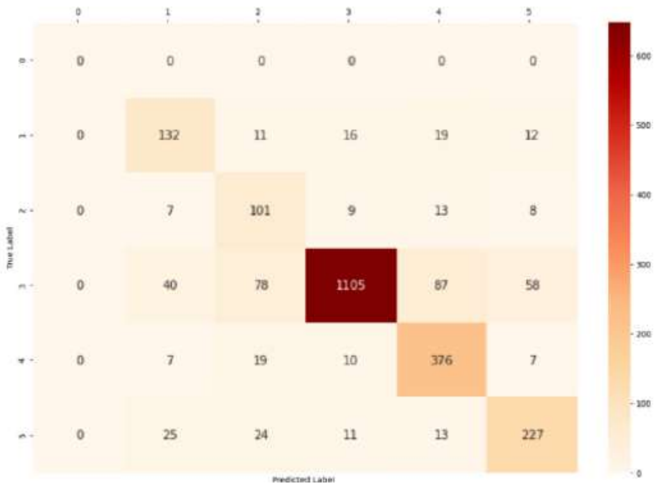

FIGURE 13. Confusion matrix after testing process

In the above confusion matrix / heatmap (Nétek, Pour, and Slezakova), the labels are numbered from 1-5.A heatmap is a colour-encoded matrix representation of rectangular data. It accepts a 2D dataset as a parameter. This dataset may be transformed into an array. This is an excellent approach to depict data since it may highlight the relationship between variables such as time. Label 1 represents wheat, 2 represents barley, 3 represents canola, 4 represents lucerne, and 5 represents minor grain crops. Hence, by comparing the different accuracy levels before and after fusion, it has been proven that after implementing the layer-level fusion technique, the model can perform better with higher accuracy and can predict crop types accurately.

5. Conclusion

The issue of large-scale management of agricultural plots is crucial from both a political and economic perspective. Deep learning algorithms have now significantly enhanced outcomes when using data in the geographical and temporal dimensions, which are essential for agricultural research. Because the fusion approach can get around issues with both the Sentinel 1 and Sentinel 2 datasets, such as the lower number of bands in Sentinel 1 photos and shadow coverings and cloud/smog impediments in Sentinel 2 images, it has been noted that the model's performance may be improved. The combination of publicly available satellite data from the sentinel satellites, with cutting-edge remote sensing techniques can give cost-effective, accurate, and rapid information on crop extent and dynamics. PSE-TAE, a deep learning architecture that exploits both the spatial and temporal aspects of the dataset, is used in this work to harmonise Sentinel-1 and Sentinel-2 time series for crop type mapping in Cape Town, South Africa. PSE-computational power and TAE's efficiency enables quick evaluation of various model setups. To improve the performance in majority and minority classes, combined Sentinel-1 and Sentinel-2 modalities are helpful. Several types of fusion are recommended depending on the availability of class samples. Any type of fusion is sufficient in the case of classes with high representation, but layer-level fusion offers additional benefits. We went through a point where switching from the multi-layer perceptron to the semi-supervised classifier was pretty challenging. Later we were able to successfully replace the decoder and deduce the logic to replace it .The PSE-TAE system may therefore prove to be extremely helpful in resolving current farming and agricultural issues.

6. Acknowledgement

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