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Unsupervised Wildfire Change Detection Based on Contrastive Learning

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Abstract: *Wildfire is a fire disaster in the forests or on the grassland of the wasteland area, potentially destroying urban and rural properties, polluting the air, and causing global warming. The subsequent fire is more likely to appear in vulnerable areas, so the images after the last fire become the images before the next one. Thus, detecting wildfire and its affected area is significant for evaluating its ecological consequence and spatial pattern. The application background of this study is to delineate the degree of impact accurately and to provide valuable information for disaster response. This study develops a self-response system based on high-resolution multispectral imagery (MSI) from the satellite Sentinel-2, adopting an advanced deep-learning approach to detect the change of burned areas. This research proposes SimCLR using contrastive learning techniques to extract features with unlabeled models. Based on SimCLR, we create our framework, FireCLR, and apply a simple CNN to capture and compare features without artificial supervision to learn and mark the wildfire on the satellite maps. By substituting the simple CNN with more advanced ResNet and VGG networks, we further improve the accuracy and ability of wildfire delineation and analysis. Our experiment proves that the model performs well in judging the wildfire conditions and vulnerable areas with given satellite images. With further studies and extensions, this model will contribute to the worldwide detection and prediction of various natural disasters.*

Keywords: *Wildfire, SimCLR, CNN, FireCLR, VGG, Disasters*

1. Introduction

When we look back upon human history, fire is undoubtedly one of the most remarkable discoveries and successful uses of natural resources. While heating us in cold winter and helping us cook food, abusing it results in troubles and even catastrophes, which cause significant losses economically and civically. In recent years, it is easy to hear news about the wildfires in grassland and forests worldwide due to both natural disasters and human activities. Wildfires have destructive impacts on the environment and creatures, polluting water resources, eroding vegetation, increasing animal mortality, and lowering air quality around disaster areas. People predict that the overall mortality of animal directly affected by wildfire is about 3% and ranged from 0% to 40%. If a wildfire happens near places with dense human activities, it would kill many people and incur a massive stagnation of economics. In 2020, a series of wildfire happened in California, which is the highest and closest record since those wildfires before 1800s. The fires killed 33 people and caused economic losses and firefighting costs of about $21 billion in 2020. The area it burned exceeded the total area of the previous sever years. Hence, an effective way to detect wildfires is significant for predicting the disaster and minimizing the loss as much as possible. For this reason, we decided to use an unsupervised study with satellite pictures of past disasters to detect potential wildfires in specific areas. As is shown in figure 1.

Figure 1: The Texas Panhandle Wildfire in 2024 [1]

2. Related Works

2.1 The Brief History of Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) was a deep learning neural network with convulutional layers which was first introduced on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) contest. In 1998, a group proposed LeNet, a CNN used to deal with the variability of 2D shapes, with Graph Transformer Network (GTN) to help minimizing an overall performance measure. Their LeNet, which was similar with a regular CNN (Figure 6), was composed of multiple layers with convolutions and subsampling alternatively and fully connected layers at the end of the network. The researchers input the shape of the numbers and made the network to recognize the unusual, distorted numbers by selecting small portions of the number and comparing them to the standards. Although some numbers were still misidentified, LeNet had lower error rate (around 1%) comparing to other classifiers. People started to realize that CNN were effective in image comparison and classification [2].

Later, after more than ten years of silence due to the prevalence of support vector machine algorithm (SVM), as the introduction of ReLU and DropOut, CNN was back in front of us. Since AlexNet in 2012, more new networks were proposed in ILSVRC every years. For example, Visual Geometry Group (VGG) of University of Oxford won the second place on the ILSVRC 2014 for their improvement. They used an architecture with very small (3×3) convolution filters to replace larger filters. They applied two small filters to substitute a 5×5 filter and three small filters to substitute a 7×7 filter, which decreased the training parameter while keeping the receptive field. They stressed the significance of the representation depth and made CNN usually reach more than ten layers. For deep CNN for large-scale image classification, their model could classify images more accurately [3]. In the next year, ResNet, the model winning first place on the ILSVRC 2015, solved the problem that CNN with more layers had higher training and testing error rate. They replaced plain network with residual learning, which allows data skip several convolution layers. Through experiments, they concluded that residual networks (ResNet) had lower error rate, and more-layer residual networks were even more accurate than less-layer residual networks though the situation is inverse for plain networks. This research gave security to a future development of CNN with over 1000 layers in more advanced studies [4]. CNN continued to develop in recent years and gradually became a popular deep learning technique which laid the base for other studies.

2.2 General Supervised Change Detection Studies

Many studies illustrated the significance of wildfire detection and the usage of deep learning technique on satellite images. Some researchers used streaming data processing and deep neural networks to locate wildfire in pixel level and create visible demonstration for experts. To improve the accuracy of the detection, one way was to enlarge the sample space. For example, a Brazilian group captured Landsat-8 images over the world and performed a CNN to detect the characteristics of wildfire. The other groups focused on improving the imagery analysis technique, the usage of PRISMA (Hyperspectral Precursor of the Application Mission), for instance. However, a simpler and more common way was to create a sample and transfer it to new samples. Adopting remote sensing technique, a German group of researchers detected wildfire and evaluated multiple indexes with a self-organized map and an artificial neural network. Remotely sensing proxy indicators from MODIS observations helped the group to monitor changes related to wildfire disturbances. Similarly, another group elaborated a transfer learning technique with a small pre-trained set of drone image. Another Indian study illustrated the excellent performance of transfer learning on limited datasets by choosing two pre-trained models and comparing them with full model training. Validated maps of past burned areas with a CNN should be required for detection and delineation of wildfire. Despite the multispectral remote sensing data and the fully developed deep learning system, labels was required in all supervised studies.

2.3 The Application of U-Net in Supervised Change Detection Studies

Deserved to be mentioned, U-Net became an universal approach of data segmentation process of supervised deep learning networks. After we input an image to a U-Net, it could return a similar image with marked segments based on our trained model. The researchers applied U-Net and other approaches to analyze burned areas from their uni-temporal MSI [5]. Another group captured Geostationary and Low Earth Orbit Satellite (GEO and LEO) images and processed the data in a deep learning model composed of a pre-trained U-Net CNN [6]. Moreover, an advanced and complicated model, Double-Step U-Net

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(DS U-Net), prevailed in many relative studies. DS U-Net was composed by two steps, binary class U-Net and regression U-Net, according to its name. The pre-trained model of binary class U-Net marked given images in black and white based on the situation of wildfire. Then, the binary image combined with the original image, used for training and validating regression U-Net. One Italian group designed a DS U-Net to delineate affected areas and estimate wildfire severity [7]. Another group applied the same method and proved it to be powerful for multiple geological contexts [8]. These methods and networks would be helpful for other supervised wildfire detection and estimation.

2.4 Unsupervised Change Detection Studies

Recently, despite the advantages of supervised deep learning networks, unsupervised networks became a promising direction to explore. The application of contrastive learning did not require labeled sets of data, large and magnificent images, or pre-trained models. Some pioneer studies created the possibilities for reference of our study although we might differ in models. At least two images for each location for pre-fire and post-fire were required in the research because the machine needed to extract differences between them to accumulate the features [9]. The exploitation of features was necessary, so regardless of the origins of the images, bi-temporal images provided the machine to find the distinctions, causing the studies with uni-temporal images limited in supervised networks [10]. The Burned Area Estimation through satellite tiles (BAE) algorithm applied Z-score normalization after capturing colors of the pictures, which further illustrated the comparison between bi-temporal images [11]. One group employed contrastive learning technique SimCLR to perform the unsupervised wildfire delineation, which was the main prototype on which this study planned to develop [12].

3. Goal

In this project, we deployed contrastive machine learning to collect the geographic information of burned areas to prepare the future wildfire in vulnerable regions and search for new potential parts. We applied unsupervised learning technique to get marked maps of areas of wildfire by inputting satellite images into the machine. Similar to the Wildfire Map app from the European Space Agency (ESA), we aimed to improve the worldwide detection of wildfires as well as delineation of range of impact and to help international fire rescue.

4. Method

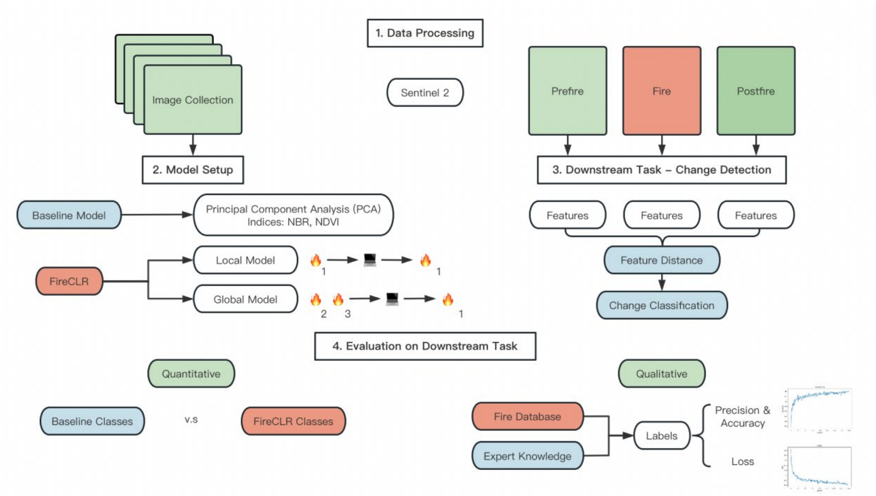

Figure 2: The diagram of the methodology

4.1 Data

We used the images from the satellite Sentinel-2 as our data sources since it had a multispectral imagery (MSI) 786 kilometers above the earth. Sentinel-2 captured 13 multispectral bands with a breadth of 290 kilometers, imagery of ground resolution of 10 meters to 60 meters, and a revisit period of 5 days. From visible lights to infrared lights, Sentinel-2 had different spatial resolutions. From the optic database,

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the data from this satellite was the only data with three distinct bands in the red edge range, which was especially effective in detecting the health condition of the vegetation. Specifically, we found a group of four-banded Sentinel-2 images including a total area of 320 squared kilometers at eight snapshots of the Mesa fire from distinct time periods in 2018. These eight images were composed of 941,190 tiles of 32×32 pixels in total. As is shown in figure 2.

4.2 Data Processing

After we acquired the data from the Sentinel-2, we got a group of eight tiff documents including multiple bands of satellite images from July to September, 2018. To make them visible, we edited code by setting the width, height, and shape of the images and showed the images of different days. We also set the number of bands (red, green, and blue) to create the color synthesized image. Besides turning the original documents to pictures that allow us to check them visually, a more important step was to convert the resources to the type of document for the machine. We compiled code to set up the tile and stride of the images and split the picture to tiles composed of pixels. Our method was to use contrastive learning to let machines obtain informative descriptions of tiles of data we have processed. Before we introduced the specific steps toward the results, we should define some concepts and indexes using in this project. As is shown in figure 3.

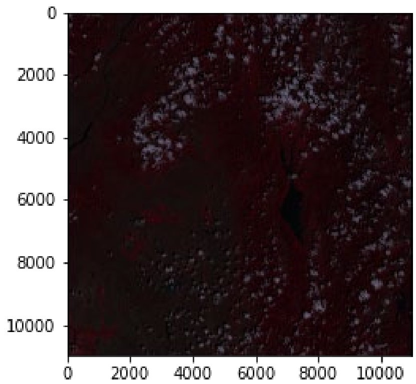

Figure 3: The example (July 1, 2018) of processed satellite images in different time

4.3 Activation Function

Activation function is a function added to the artificial neural network, helping the network to learn complex modes of data. Activation function can introduce nonlinear factors to allow every layer of the neural network to perform nonlinear transformation rather than only linear transformation. With activation function, the neural network can learn some smooth curves to cut the plane rather than linear combinations, which improve the neural network's ability of expression since these curves match the objective function better. The activation function in CNN is Rectified Linear Activation Function (ReLU), which is proved to be one of the milestones in deep learning development. ReLU is a simple calculation: if the input is greater than zero, it just returns the input; otherwise, it returns zero. For values that are greater than zero, this function is linear, meaning that ReLU has many ideal characters of linear functions when training CNN with back propagation. Due to its simplicity of calculation and both linear and nonlinear behaviors, it becomes more popular and activates the development of new models of CNN. As is shown in figure 4.

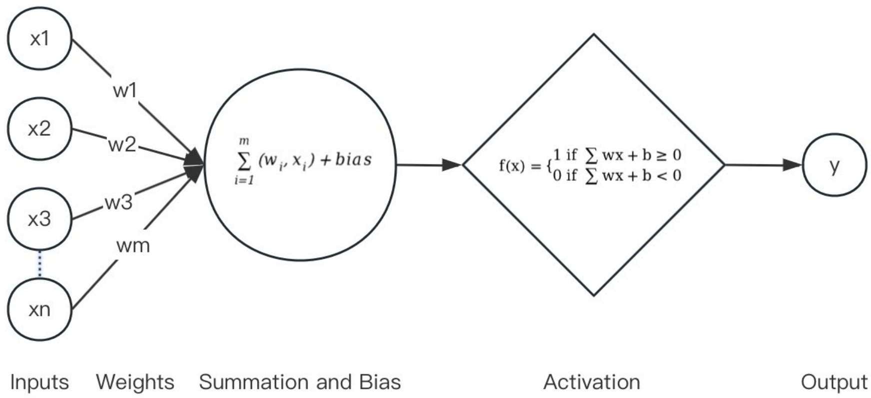

Figure 4: Activation function in the neural network

4.4 Normalization

Normalization is the process that converts all data to numbers in [0,1] or [-1,1] to eliminate the difference of orders of magnitude between various dimensions of data. This process avoids large error of network prediction due to the large difference of orders of magnitude. It unifies the dimensions of data and speeds up the program operation. There are four main types of normalization:

1) Linear normalization

Linear normalization is also called max-min normalization or discrete normalization, which is the linear transformation of the original data. Here is the equation:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

This normalization is the easiest way to eliminate the effects of dimensions and ranges while keeping the relationships in the original data. However, if the maximum and the minimum are unstable or too far apart, this way becomes less reliable.

2) Z-score normalization

Z-score normalization is also called standard deviation normalization, so the mean of the processed data is 0 and the standard deviation is 1. The equation is shown below:

$$x' = \frac{x - \mu}{\delta}$$

μ is the mean of the original data, and δ is the standard deviation.

This method normalizes the mean and the standard deviation of the original data. The processed data conforms to the standard normal distribution in this way of normalization.

3) Decimal scaling normalization

This normalization is moving decimal places of the original data to map them to [-1,1], which depends on the maximum absolute values among the data. The equation is that:

$$x' = \frac{x}{10^k}$$

4) Nonlinear normalization

This method includes logarithms, exponential, and tangent normalization, which are used in dealing with large scales of data.

4.5 Data Augmentation

Data augmentation is a key process in the SimCLR model by transforming data to enlarge their variation. It can increase the number of the training data, avoid the unbalance of the sample, prevent over-fitting, and improve the robustness and generalization ability of the model. Some typical data augmentation settings and transform functions are listed below:

1) Random horizontal flip

To flip the images horizontally, which forms a bilateral symmetry (pixels move to the horizontal counterpart)

2) Fixed rotation transform

To rotate the images around a certain point, either the origin or any point on the plane (the lines connected to the rotation point and pixels rotate certain degrees)

3) Gaussian Blur

To smooth the colors and lines in the images to reduce their details (the central pixels become the average of the pixels around them)

4) Random resized crop

To cut the images along certain lines

5) Interpolation mode

To relocation parts of the images

4.6 Contrastive Learning

Contrastive learning is a kind of unsupervised learning, by which machines identify objects without artificial marks. The machine studies the similarities in the same categories and differences between different categories in a few distinct datasets by applying data augmentation on each image. The purpose of contrastive learning is to mimic an encoder which codes same types of data similarly and various types of data as different as possible. Comparing to generative learning with encoders, contrastive learning avoids complex details on the specific images and just distinguish them on the abstract level. Thus, the models and optimization of contrastive learning are easier and better at generalizing to other events. In this study, we use contrastive learning to replace the manual labeling process in common supervised learning. As we mention above, we adopt an advanced model, SimCLR, recently proposed by Google Brain.

Loss function is the difference between the predicted value and the actual value of each sample through the model. Contrastive loss function is the loss function with self-discovery of complex negative samples, which is crucial for learning high-quality unsupervised expression. The purpose of focusing on complex samples is to distance close samples from each other to improve its uniformity. The temperature coefficient exists in a loss function and adjusts the attention to complex samples. A smaller temperature coefficient can separate the sample with other similar samples to create a more uniform distribution. A common loss function with a temperature coefficient used in contrastive learning is info_NCE:

$$L_q = -\log \frac{\exp(q \times k_+ / \tau)}{\sum_{i=0}^{K} \exp(q \times k_i / \tau)}$$

k is the positive sample of q, q is the negative sample of itself, and τ is the temperature coefficient.

Algorithm 1: Info_NCE in the loss function

```
labels = torch.cat([torch.arange(batch_size) for i in range(n_views)], dim = 0)
labels = (labels.unsqueeze(0) == labels.unsqueeze(1)).float()
labels = labels.to(device)
features = F.normalize(feature, dim = 1)
similarity_matrix = torch.matmu(features, features.T)
mask = toech.eye(labels.shape[0], dtype = torch.bool).to(device)
labels = labels[~mask].view(labels.shape[0], -1)
similarity_matrix = similarity_matrix[~mask].view(similarity_matrix.shape[0], -1)
positives = similarity_matrix[labels.bool].view(labels.shape[0], -1)
negatives = similarity_matrix[~labels.bool].view(similarity_matrix.shape[0], -1)
logits = torch.cat([positives, negatives], dim = 1)
labels = torch.zeros(logits.shape[0], dtype = torch.long)
logits = logits / temperature
```

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return logits, labels

We define labels by categorizing the batches and assert the similarity matrix of the shape being the same as labels of the shape. We select and combine the loss of the positive samples in (N, 1) and merely select negative samples in (N, K). Then, we perform categorization and make the samples divided by the temperature coefficient, which controls the concentration level of distribution, to get logits in (N, 1+K). The goal is to get 1 for the positive samples and 0 for the negative samples, so we categorize logits in (1+K) categories and set labels as 0.

Algorithm 2: Computing loss of a set of images

Input: A set of images describing the wildfire condition in one area

for *image in tqdm(train_loader)*

features = model(images)

logits, labels = info_nce_loss(features)

loss = CrossEntropyLoss(logits, labels)

With the info_NCE calculated above, we use cross entropy loss to calculate our loss function.

4.7 Model Setup

Before going into the experimental steps of this project, we developed two related models, baseline and machine learning models, and we conducted NBR and NDVI for the baseline models. For this project, which was hard to extract the characteristics and label our aimed object (wildfire) by humans, we considered using self-supervised learning. We applied contrastive learning, a specific approach of self-supervised learning, in detecting wildfire because we had easily collected and prepossessed images before and after the fire. To be more specific, we utilized a well-developed method, SimCLR, to provide a framework for the experiment. SimCLR generated two augmentations from the same image, which changed the color, direction, size, and other parameters of the image. Then, the machine extracted the features of both augmentations and organized them as the input elements in CNN. The advantage of a CNN was to utilize the 2D structure of the input images, so it was efficient especially when dealing with plane datasets. The CNN was more suitable for processing the data than other networks since it was easier to train and has fewer parameters. In the convolutional layers, machines marked the pixels of input images with numbers (usually positive or negative ones) to study the different features of the original picture. The fully connected layer, which existed in the last part before the output layer, organized the results from the convolutional layers by judging whether the features were true or false. It reduced the dimensions to record them in one dimension and led to a small fully connected neural network. Finally, the machine projected data into another vector space and found the value of the loss function by computing cosine similarity.

Based on the original SimCLR model, we applied another framework, FireCLR, from a previous research to better fit our wildfire detection program. FireCLR used only a simple CNN and worked for images of multispectral bands rather than merely RGB images, which fitted this study better. Based on the satellite images of wildfire, the FireCLR machine changed them with different shapes, directions, and colors and produced multiple distinct pictures with the same frame. With regard to each pair of images, the machine split them into small parts and put them into a CNN like the one in SimCLR above. For example, the machine selected a small area, about a few trees, from the satellite image with wildfire and put it into the first convolutional layer. Through the continuous splitting process of CNN, in the fully connected layers, the machine could figure out the wildfire features by comparing minute parts with the image and marking true or false. With the processed data in one dimension, the machine was almost able to detect wildfire in an satellite image describing another area. For this research, specifically, we used this formula to calculate the wildfire situation and changes for satellite images from the FireCLR model:

$$\mathrm{S}(x) = \mathrm{d}(\mathrm{f}(x_{t_1}), \mathrm{f}(x_{t_2}))$$

In this formula, x_{t_1} and x_{t_2} represented the extracted part of the location x in two different time, t_1 and t_2. Function $\mathrm{f}(.)$ was showed in the diagram under the definition of SimCLR, and we used cosine distance for function $\mathrm{d}(.)$. In the training using FireCLR, we input a group of four-banded Sentinel-2 images including a total area of 320 squared kilometers at eight snapshots of the Mesa fire from distinct time periods. It tiled them into 941,190 tiles of 32×32 pixels and trained the model for 200 epochs. We showed the result of the data training by the accuracy curve and the loss curve in the evaluation section (3.4). Finally, we could bring these results and formulas to our downstream task, detection of wildfire changes.

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5. Results

5.1 Downstream Task - Change Detection

By going through the same process described in the data processing section (3.1), we processed other two tiff documents as the validation of our data training results. These documents were Sentinel-2 snapshots from July 26th and August 15th, 2018 during the time range of those eight training documents, showing the same area before and after the wildfire respectively. Due to difficulty of taking picture during the fire, we did not have the image in the middle of the Mesa fire. In the validation process, FireCLR captured the features in those images and followed the same path of training through CNN without manual annotations of the snapshots. It tiled them into 118,980 tiles and 114,828 tiles for each tiff document and validated the model for 200 epochs. In the first few epochs, fortunately, the accuracy already reached more than 90%, and the loss was less than 0.5, which indicated that our previous training regarding this site succeeded. To visualize the results, we input the satellite images into the model and used k-means to cluster the results. The pictures of two, three, and five clusters are shown below with respect to one wildfire image. Besides, if we had more time, we would deployed it to a global level, which meant that FireCLR could detected the situations before and after wildfires in other locations. For the snapshots of these places, the detection should also not require manual labels beforehand. As is shown in figure 5.

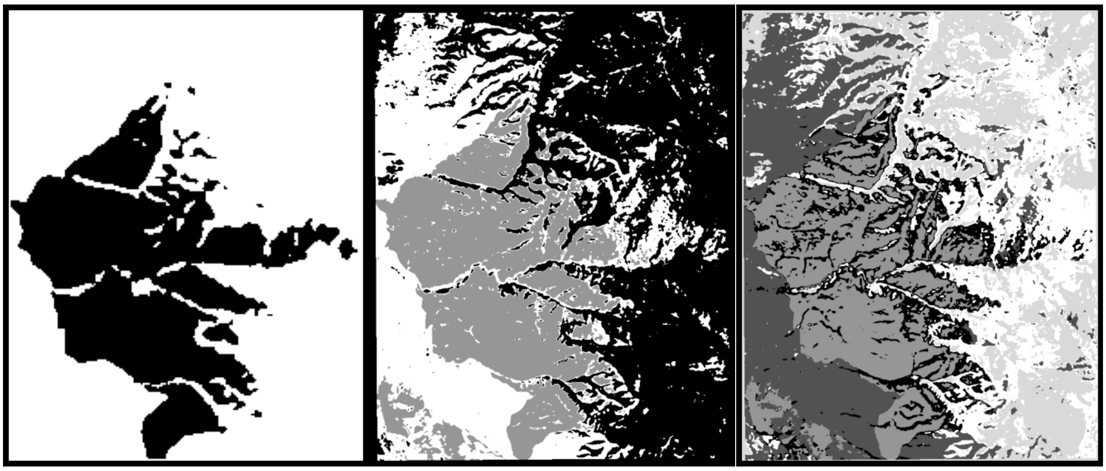

Figure 5: Results: marked area with two, three, and five clusters respectively

5.2 Evaluation on Downstream Task

In the downstream task, extracting discriminating and meaningful features from both snapshots was the most significant job for FireCLR, and we evaluated its job by calculating the difference between them. With Euclidean and cosine distance we calculated, it classified the feature distance to various categories such as black ash, white ash, and unaffected regions. The more cosine similarity the model got, the higher accuracy and precision and the lower lost it had. Then, based on the approach and pseudo codes introduced in Definition 3.11, we made the accuracy curve and the lost curve presented below. The accuracy mainly increased and just reached above 90% in the final epochs, which was satisfactory for the SimCLR model with the simple CNN in the first trial. The loss kept under 1.0 and sometimes approaches 0.5 from the initial values of more than 1.5, which also indicated the feasibility of SimCLR. Because of the CNN inside the model and the limitation of training, we could improve the accuracy and loss by replacing this with more advanced CNN or increasing the number of epochs. Furthermore, we could even change SimCLR, a model based on contrastive learning, to RaVAEn, a system based on generative learning, without turning the project into a supervised experiment. As is shown in figure 6.

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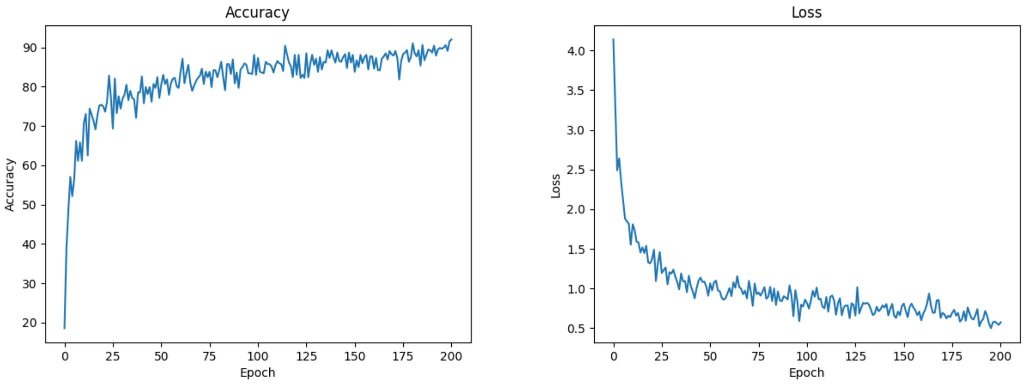

Figure 6: The accuracy and loss curves of SimCLR

6. Discussion

6.1 Other Convolutional Neural Networks (CNN)

Since the attempt of replacing a contrastive learning model with a generative learning encoder failed for this project, we decided to replace the simple CNN in SimCLR with other forms of CNN. The training and validation processes went normally, and we used the same method to calculate their accuracy and loss curves. As we introduced in 2.1, the VGG network could lower the training parameter, which enabled CNN to include more layers. However, the results of VGG-16 did not display obvious accuracy changes since they maintained 100% in all times, so there was no clear trends on the loss curve either. Then, we tried ResNet-18, which showed better trends and data than SimCLR with accuracy greater than 90% and loss lower than 0.4 for most of the epochs. The accuracy increased along the training process, and the loss decreased correspondingly. For further improvement, we changed ResNet-18 to a CNN with four convolutional layers, which gave better results in the first few epochs. Although the final results are similar, this model was faster to become accurate than ResNet-18. Due to the high beginning, this model did not have much space to improve, but the overall accuracy and loss were great enough to make the model provide information for most wildfire in the world. As is shown in figure 7, 8 and 9.

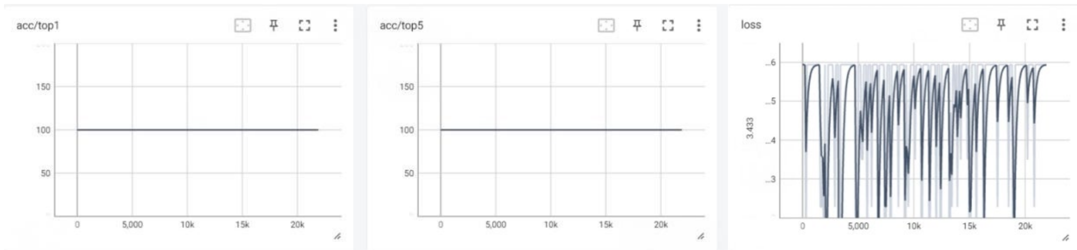

Figure 7: The accuracy and loss curves of VGG-16

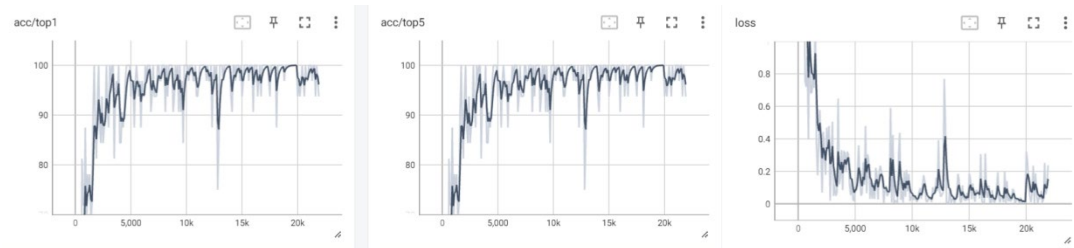

Figure 8: The accuracy and loss curves of ResNet-18

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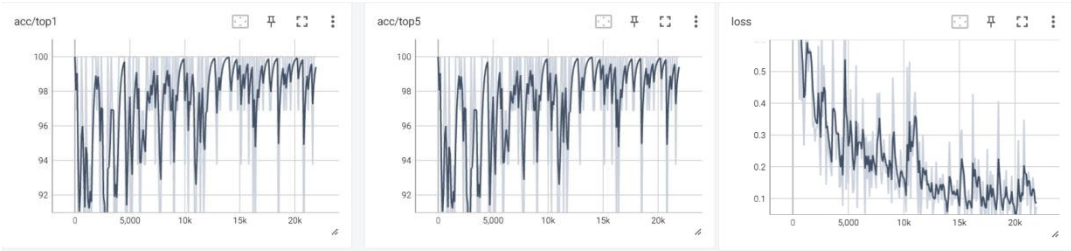

Figure 9: The accuracy and loss curves of four convolutional layers

7. Conclusions

With the results from the evaluation part, we concluded that SimCLR and its replacements were effective for unsupervised wildfire change detection. The FireCLR model could delineate the wildfire condition and detect the affected areas based on given satellite images. Despite the accuracy and efficiency of the model, the training process of contrastive learning for wildfire is required for the estimation of the same disaster. Thus, we had to provide more information of other disasters for it to develop a wider application on disaster response. In future study, we would attempt to apply a VAE to improve the machine's adaptive ability. We could also adopt a more advanced satellite image processing mechanism to marked the affected area in a unified form. Continuing the unsupervised technique, we expected to improve the worldwide disaster prediction and response ability.

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