HardMax

CE 784A Project Report: Semester 2022-23 (II)

Wildfire Spread Prediction

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Abstract

Wildfires are a major environmental and socio-economic challenge that require accurate prediction of their spread and extent. In this paper, we analyze the wildfire spread data and methods for predicting the wildfire spread extent map for the next day using the current spread images and various features such as topography, wind direction and temperature. We discuss two methodologies for prediction approach, the first method is pixel-based, where each pixel is treated as a separate data point making it a binary classification problem where a simple model can be trained to classify the pixel as part of the wildfire or otherwise. The second method is convolution-based, where we use deep learning convolutional neural network (CNN) models such as U-Net and SegNet to segment the wildfire images. We will run the model on the dataset of 64 Km x 64 Km images with 1 Km spatial resolution and evaluate the model based on the benchmarks for accuracy, precision, recall and F1-score. We also discuss the advantages and limitations of each method and suggest directions for future research.

Keywords: Wildfire, Convolution, U-Net

1. Introduction

Wildfire spread prediction is a crucial task for preventing and mitigating the devastating effects of wildfires. In recent years, machine learning algorithms have been applied to wildfire spread prediction with promising results. These algorithms can analyze various factors that influence wildfire behavior, such as weather conditions, topography, and vegetation, to forecast the direction and speed of fire propagation. One popular approach is to use neural networks to learn patterns in historical wildfire data and use that information to predict future behavior. Additionally, machine learning algorithms can be integrated with remote sensing technologies to provide real-time monitoring and early warning systems. By leveraging the power of machine learning, wildfire spread prediction can be significantly improved, enabling better planning and response strategies to protect both human lives and the environment. The factors that we have considered that can influence the occurrence and severity of wildfires are drought, population density, elevation, vegetation, and weather conditions. Here is how each of these factors is related to wildfire:

- **Drought**: Drought conditions can dry out vegetation, making it more susceptible to catching fire. Drought can also increase the frequency and intensity of lightning strikes, which can ignite wildfires. In addition, drought can lead to water shortages, which can make it more difficult to fight wildfires.
- **Population density**: Areas with high population density are more likely to experience wildfires because there is a greater chance of human-caused fires. Additionally, as more people move into wildfire-prone areas, the risk of property damage and loss of life increases.
- **Elevation**: Elevation can affect the temperature and moisture content of vegetation, which can impact the likelihood of wildfires. For example, areas at higher elevations are generally cooler and more moist, which can reduce the risk of wildfires.

- **Vegetation**: The type and density of vegetation can influence the likelihood and severity of wildfires. Areas with dense, highly flammable vegetation are more prone to large, intense wildfires. In contrast, areas with sparse vegetation or low-flammability vegetation are less likely to experience large wildfires.
- **Weather conditions**: Weather conditions such as high temperatures, low humidity, and strong winds can increase the risk of wildfires. For example, hot and dry weather can dry out vegetation, making it more susceptible to catching fire. Strong winds can also spread wildfires quickly, making them more difficult to contain.

In summary, wildfires are influenced by a combination of factors including drought, population density, elevation, vegetation, and weather conditions. Understanding these factors is important for assessing wildfire risk and developing strategies to prevent and manage wildfires.

2. Literature Review

As we can realize that forest fire prediction is issue of great importance, there is a lot of recent literature available where author have used various artificial intelligence technologies and modern computational techniques to predict forest fires. Deep learning was used by many scientists to forecast the spread of wildfires from remotely sensed data, including usage of extracted elements from satellite photos using a convolutional neural network (CNN) then projection of wildfire spread using a recurrent neural network (RNN).

A CNN was used to identify fire profiles from security camera video in ”Early fire detection using convolutional neural networks during surveillance for effective disaster management” by (Muhammad et al., 2017). The authors employed a pre-trained CNN as a feature extractor and then trained a fully connected neural network on top of it to determine whether or not a frame included a fire. Deep learning was used in ”Deep Learning for Forest Fire Prediction Using Remote Sensing Data” (Zhang et al., 2016/01) to forecast forest fires using remote sensing data. The authors extracted elements from satellite photos and predicted the chance of a fire beginning in a certain place using a mix of CNN and RNN models. (Ananthi et al., 2022) suggested ”Forest Fire Detection and Prediction Using Artificial Intelligence and IoT” a system for forest fire detection and prediction utilising AI and Internet of Things (IoT) technology. Machine learning techniques were employed by the authors to detect abnormalities in temperature and humidity data and forecast the chance of a fire beginning in a certain place. (Naga Saranya and Hemalatha, 2012)'s ”Integration of machine learning algorithm using spatial semi supervised classification in FWI data” employed a combination of machine learning and deep learning approaches to predict forest fires. The scientists identified the most essential parameters for forecasting forest fires using a decision tree approach and trained a deep learning model to predict the risk of a fire beginning. (Shreya et al., 2023) employed a deep learning technique in ”Forest Fire Prediction Using Machine Learning and Deep Learning Techniques” to predict the occurrence of forest fires. A recurrent neural network (RNN) was utilised by the authors to assess historical meteorological data and estimate the possibility of a fire beginning in a certain region. (Goetz et al., 2006) 's ”Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada” employed a mix of AI and time series analysis to predict forest fires. The scientists used historical meteorological data to forecast the chance of a fire beginning in a certain place.

We have used the U-NET, The U-Net architecture is a deep learning network designed primarily for picture segmentation. (Ronneberger et al., 2015a). introduced it in their paper ”U-Net: Convolutional Networks for Biomedical Picture Segmentation” in 2015. Since then, the U-Net has been widely used in a wide range of applications, including medical picture segmentation, road detection, and many more. (Zhou et al., 2018) suggested a modified U-Net design with layered skip connections in ”U-Net++: A Nested U-Net Architecture for Medical Image Segmentation” to increase the performance of medical image segmentation tasks. In various medical picture segmentation tasks, the U-Net++ design outperformed the original U-Net architecture. (Iglovikov and Shvets, 2018) suggested ”TernausNet: U-Net with VGG11 Encoder Pre-Trained on ImageNet for Image Segmentation,” a modified U-Net architecture with a VGG11 encoder pre-trained on ImageNet. The authors demonstrated that pre-training the encoder using ImageNet increased the U-Net architecture's performance in multiple picture segmentation tasks.

”Connected-UNets: a deep learning architecture for breast mass segmentation” by (Baccouche et al., 2021) employed a hierarchical U-Net architecture to separate breast masses in mammography pictures. The authors demonstrated that their modified U-Net architecture outperformed the original U-Net and other cutting-edge segmentation networks in multiple breast mass segmentation tests.

We will be referring to (Huot et al., 2022)'s "Next Day Wildfire Spread: A Machine Learning Dataset to Predict Wildfire Spreading From Remote-Sensing Data" as a basis for our research work. We will be employing Mask R-CNN which is a prominent deep learning model that relies on the Faster R-CNN model for object identification and instance segmentation. The following are some major conclusions from numerous research articles that employed Mask R-CNN: (He et al., 2017a) published "Mask R-CNN," which presented the Mask R-CNN model and proved its usefulness for segmentation on the COCO dataset. The authors demonstrated that Mask R-CNN outperforms earlier approaches on numerous benchmark datasets and is substantially quicker. In paper "DeepLesion: Automatic Mining of Large-Scale Lesion Annotations and Universal Lesion Detection with Deep Learning," (Yan et al., 2018) employed Mask R-CNN to identify lesion in medical photos. With their dataset, the authors proved that Mask R-CNN outperformed other state-of-the-art approaches for lesion identification. Overall, these studies demonstrate that Mask R-CNN is a powerful deep learning model for object detection and instance segmentation that has been successfully applied to a variety of tasks such as biological image segmentation, object detection on resource-limited devices, and medical image analysis.

3. Dataset

Our dataset primarily comprises of examples each of 64km x 64km at 1 km resolution. Each row in the example dataset represents a specific time and location where a fire took place, and the columns represent various variables such as weather, drought, vegetation, population density, etc. There are 18545 samples in our final dataset. The size of the fire rises in 58% of these samples (10798 samples) from time t to time t + 1. In 39% of the samples (7189), the fire gets smaller. The fire maintains its size in the remaining samples.
Wildfire mask data is taken from MOD14A1 V6 dataset provided by NASA LP DAAC at the USGS EROS Center, and elevation data is taken from the SRTM. Drought and weather conditions data are taken from GRIDMET dataset provided by University of California at Merced. Vegetation data is provided by NASA LP DAAC at the USGS EROS Center and population density dataset is taken from the Gridded Population of World Version 4 (GPWv4) dataset.

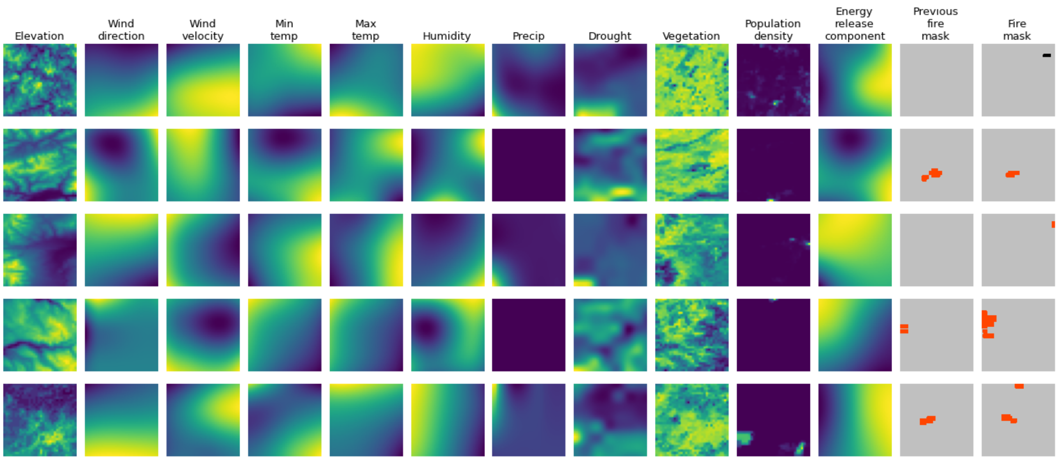


Figure 1: Visualisation of data with features

4. Methodology

In this problem, we are given various geospatial features like topography, wind direction, temperature information for a given time as well as the extent map of the wildfire spread at that given time, and we have to predict the extent map of the wildfire at next day. Thus we can treat it as a segmentation task.

The dataset we have been provided has a spatial resolution of 1 km, which means that each pixel on the image represents a 1 km x 1 km region. And all the geospatial data and maps that have been provided represent a 64 km x 64 km region of a fire event.

4.1. *Pixel Based Method*

We can consider each pixel as a separate data point and use corresponding pixels information from all the geospatial data, making it a binary classification task for each of the pixels trying to predict if there would be wildfire at the location of that pixel or not. These are primarily non-deep learning models that don't leverage the 2D information i.e. they don't take into consideration the relation of a pixel to its neighbouring pixels.

4.2. *Convolution Based Method*

In this approach we leverage the 2D information by using convolutions and thus using a deep learning CNN based model. There are various deep learning models for segementation like U-Net, SegNet and Mask RCNN (Ronneberger et al., 2015b; Badrinarayanan et al., 2015; He et al., 2017b). The CNN based models which perform segmentation typically use an encoder-decoder structure where the encoder is followed by bottleneck and a decoder or upsampling layer directly after bottleneck. The input for the model is geospatial information and wildfire mask of that day concatenated forming (D+1) x 64 x 64 dimentional input where D is the no. of geospatial features. This architecture first squeezes the input information into a form of latent vector which is then passed through a fully connected network to form a representation of the input. This representation is then decoded and passes through a sigmoid layer giving us the resulting wildfire map for the next day.

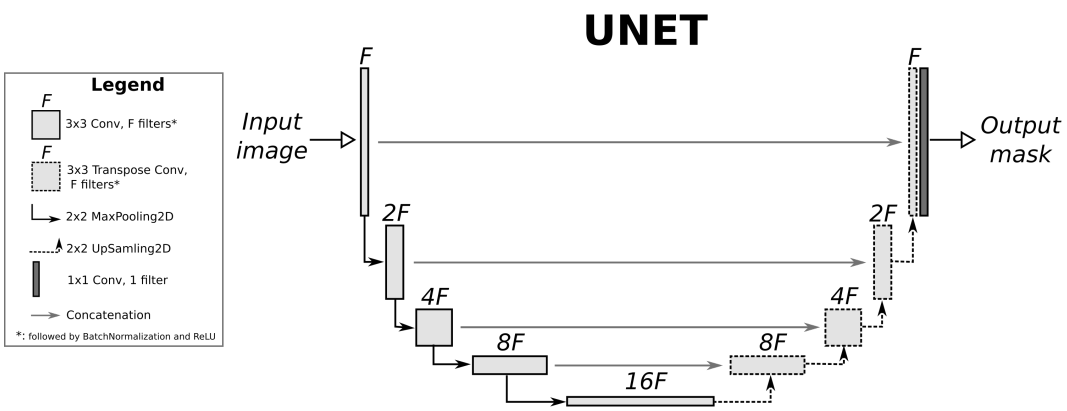


Figure 2: UNet architecture

We are planning to use U-Net architecture (Ronneberger et al., 2015b) as shown in the Fig. 2. U-Net is similar to the typical encoder-decoder framework, which first introduced skip connections in order to solve the problem for the loss of information which happens in the encoder layer in which downsampling takes place. Skip connections are the connections that go from the encoder directly to the decoder without passing through the bottleneck, in this way features at various levels are captured and concatenated to feature maps in the decoder resulting in reduced data loss.

5. Implementation

5.1. *Implementation of Neural Network*

To solve class imbalance, we first tried to use , the loss function as weighted with the WeightedCCE (Weighted Categorical Cross-Entropy) function, with weights of [0.4, 0.1, 0.5] for the three classes. but was not getting satisfactory results.

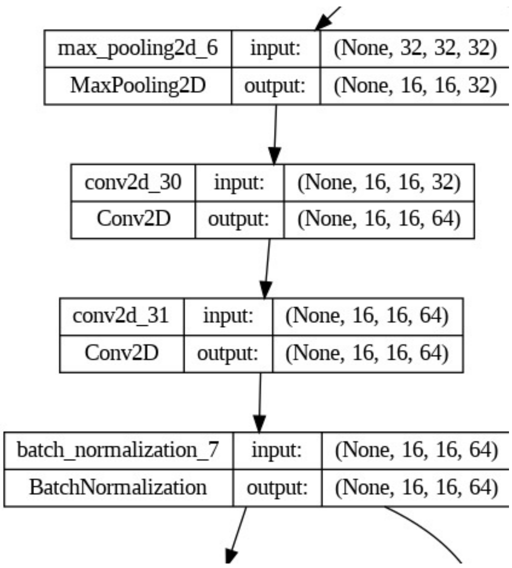
We then used SMOTE, in which the dataset (in which each pixel is a data point) is first preprocessed using the imblearn package's Synthetic Minority Over-sampling Technique (SMOTE), followed by transforming the class labels to categorical data. SMOTE (Synthetic Minority Over-sampling approach) is a prominent data augmentation approach used in machine learning to overcome class imbalance. It is especially useful when dealing with datasets in which the minority class has a much lesser number of instances than the majority class. SMOTE operates by interpolating between existing instances to generate synthetic examples of the minority class. The algorithm chooses a minority instance and searches the feature space for its k nearest neighbours. Then, at random, it chooses one of these neighbours and creates a synthetic instance by interpolating between the two instances. This procedure is continued until the desired number of synthetic instances are produced.

SMOTE's synthetic examples are not merely duplicates of current instances; they represent fresh instances that can serve to increase the model's generalisation. This is because SMOTE generates instances in the region of the feature space where the minority class is underrepresented, improving the overall distribution of the data. Overall, SMOTE is a valuable strategy for correcting class imbalance in machine learning and can enhance model performance by producing additional instances of the minority class that improve data distribution.

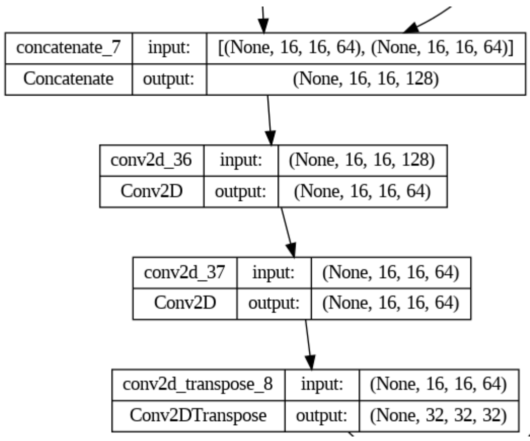
The model architecture is made up of three thick layers, the first two of which include 64 and 32 neurons, respectively, as well as a ReLU activation function. The output layer has three neurons, one for each of the three classes in the dataset, and the sigmoid activation function is utilised to calculate probability scores for each class. The loss function utilised is categorical cross-entropy, and the model parameters are optimised using the Adam optimizer. This means that throughout training, the model will prioritise accurately categorising instances of the minority class.

5.2. *Implementation of UNet*

In our implementation, we modelled encoding and decoding blocks separately, such that the functionality of encoding block was majorly encoding the features into a smaller tensor. One of the encoder block is shown in Fig. 3a, and decoder block is shown in Fig. 3b. In the encoder architecture, the additional connection leaving the batch normalisation layer is the skip connection that connects encoder to decoder, and these connection are concatenated to the decoder layer as in decoder architecture.



(a) Encoder architecture



(b) Decoder architecture

In all the CNNs, we have used ReLU as the activation function and for better initialisation we have use Kaiming initialisation which is an initialization method for neural networks that takes into account the non-linearity of activation functions. We used Adam optimizer with an learning rate of 0.001. As we were dealing with segmentation problem our final output had 3 channels which represented the probability that of that channel, and thus we used Spare Cross-Entropy loss. As the data that we were using had majority of pixels that represented "No Fire", thus we had to use weighted cross entropy loss and weights that we assigned for "Unknown", "No Fire" and "Fire" are 0.2, 0.2 and 0.6 respectively. For the deep learning model, we augmented the data using random crop, random flip and random rotation. We performed the training for the model on 2 different pixel resolution i.e. for 1 km x 1 km grid resolution and 2 km x 2 km resolution. We trained both the models on Google Colab, thus we used Tesla T4 GPU for 20 epochs. The fine-tuned the model selecting the model based on the model having the best F1 score.

6. Results

Following is the link of the code (in ipynb format)that has been used in our paper: Github Link

6.1. *Result of Neural Network*

Below are the results for neural network as we can see we are not getting goog f1 score its just 0.1 their could be various reasons for that but the prominent one is the non fire case, we tried 2 methodologies to improve this 1) using weighted cross entropy loss function that was still giving very bad results 2) to improve it we used the smote which was described earlier in which we used the technique of oversampling it gave improved results but still were not upto the mark.

	precision	recall	f1-score	support
unknown	0.07	0.22	0.10	5280
no fire	0.98	0.79	0.88	398985
too much fire	0.04	0.58	0.08	5335
accuracy			0.78	409600
macro avg	0.36	0.53	0.35	409600
weighted avg	0.96	0.78	0.86	409600

Figure 4: Prediction made by neural network architecture

6.2. *Result of UNet*

Precision and recall of Unet model for positive case (i.e. wildfire is present) on fire spread prediction per area (1 km × 1 km) is 37% and 36% respectively. Also the F1-score for this case using UNet is 0.36. Prediction made is shown in 5

We have also train the Unet model after x2 upsampling. Precision and recall of Unet model for positive case (i.e. wildfire is present) on fire spread prediction per area (2 km × 2 km) is 31% and 43% respectively. Also the F1-score for this case using Unet is 0.36. Prediction made is shown in 6

Our results score are coming to be less just because our dataset was skewed towards no fire case. In most of the pixels there was no fire and only few pixels were showing that there was fire in that region. Also the data provided to us was in .tfrecord format making it quite difficult to modify it. Despite the low metrics for the positive case (i.e. wildfire is present) , it can be observed in Figure 5 that the model successfully predicts fires in some samples. The predicted fires are usually located in the target area and have rounder shapes and smoother borders compared to the target. Additionally, the model may merge fires that are close to each other into a single fire. Also, our model heavily relies on the previous fire mask, often predicting that a previous small fire expands, even though the fire was no longer present in the target. The errors in segmentation arise from the model missing small fires and wrongly classifying pixels between fire and non-fire areas.

7. Conclusion

We were given the task of prediction of wildfire spread using the data set of examples of images of size 64 x 64 km, with 1 km resolution. We went through different literature available of the classification on images and predicting environment hazards such as wildfires and decided to choose two approaches, a pixel based approach where we could every single pixel of a image and train a neural network based on the 12 channels available as features. The model ran with a decent accuracy. We had to upsample the data as the fire zones were less in the frame. Second approach

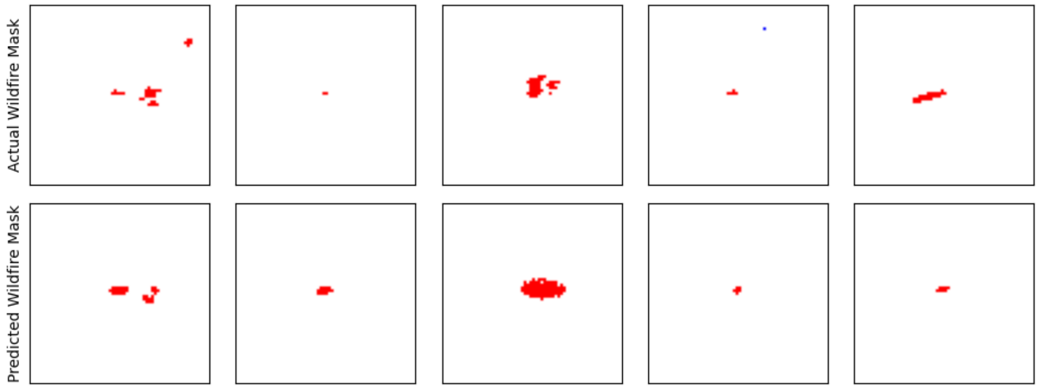


Figure 5: Prediction made by UNet model on original size

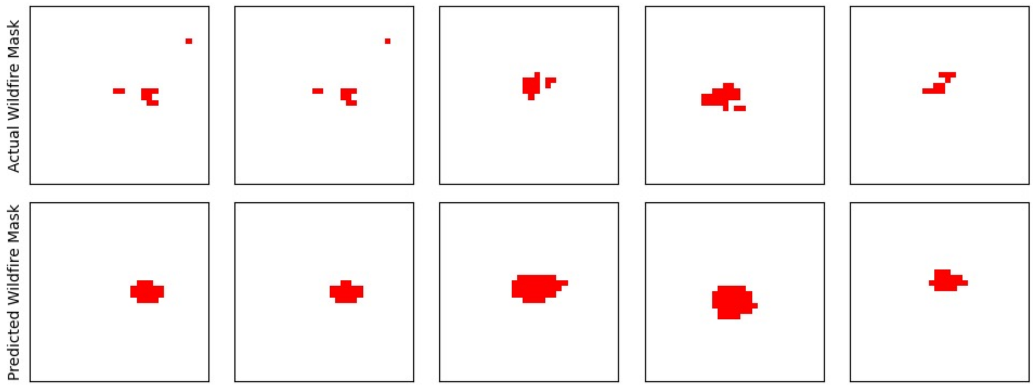


Figure 6: Prediction made by UNet model on 2x size

was of treating images as a whole and running deep learning models for segmentation like UNet, SegNet etc. These are CNN based models. We chose U-Net which was similar to the autoencoder framework, but had an additional long skip connections between encoder and decoder blocks which helps it retain fine-grained information that may be lost due to the downsampling done by the encoder blocks. The predictions done by the model based on the CNNs were much better as compared to the pixel-wise classification approach, but even those were not good enough to apply this model on a real wildfire situation. But as more types of geological satellite based data for these types of wildfire get collected the performance of would also improve. Moreover, the performance of model can also be improved by using synthetically generated data to train such model, the synthesis of such data can be carried out using GANs based generative models.

8. Work distribution

- **Ayush Gupta:** Studied various methods and model architecture, Coding: U-Net implementation and fine-tuning, U-Net experimentation, Report writing (Methodology and Implementation section)
- **Aryash Pateriya:** Studied scientific causes of wildfire and feature preference for prediction, Report writing (Abstract and references section), coding : neural network part and report writing (neural network and their results)

- **Mohammad Imad Khan:** Studied the selected methodologies and their implementations, Report writing (Literature and reference section), coding : neural network part and report writing (neural network and their results)
- **Roushan Prakash:** Data processing and data visualisation, Coding (Data loader section and metrics for U-Net), Report writing (Introduction, Dataset section and results for U-Net)

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