Landfill Net: A Convolutional Neural Network (CNN) Architecture for the Detection of Landfills from Satellite Imagery in the Continental United States

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Abstract

As we continue through the 21st century, the effects of climate change have become more and more apparent, with methane emissions playing a pivotal role as one of the most potent greenhouse gasses. Landfill decomposition is a large contributor to this rise in methane, and certain landfills have even adopted methane capture systems that enable the conversion of this methane into valuable energy resources. To continue to mitigate these emissions, it is imperative to establish a comprehensive United States landfill database. I present a Convolutional Neural Network (CNN) model that uses image data in the United States to distinguish whether an image is a landfill or not. The model had a test accuracy of 97.1%, a precision of 96.3%, a recall of 98.1%, and an F-1 score of 97.2%. The results show that the model holds the potential to uncover illegal landfills within the United States and facilitate an informed expansion of methane collection systems in landfill sites.

Introduction

Climate change is an imperative issue of our time, and the consequences of rising temperatures and sea levels have an unprecedented effect on a global scale. Methane emissions are at the forefront of climate change, accounting for 25-30% of the global warming we are experiencing [1]. In fact, methane traps 80 times more heat in the atmosphere than carbon dioxide, ultimately making it much more dangerous. [2]

Methane is emitted from various human-influenced sources, one of which is from the decomposition of landfills. According to the United States Environmental Protection Agency, "MSW landfills are the third-largest source of methane emissions in the United States generated by human activity, accounting for approximately 14.3 percent of these emissions in 2021"[3].

The agency has adopted a program called LMOP (Landfill Methane Outreach Program) that seeks to collect methane emitted by landfills and turn it into renewable energy. However, the current database of landfills has its limitations. Most of the data is outdated, meaning that there are many inactive landfills present in the data and unrecorded landfills that have not been documented in the database. Additionally, since the data is dependent on government-reported landfills, the database cannot document illegal dumping sites.

Through this research, I have curated a comprehensive dataset using satellite images of active landfills and trained a supervised classification convolutional neural network [4]. The ResNet machine learning model used this imagery data to classify whether images contained landfills, and model metrics were evaluated to assess the model's performance [5]. The success of this model has given it the potential to promote an informed expansion of LMOP projects and identify undocumented landfills in the United States.

Background

Currently, there is no existing work on landfill identification in the United States, specifically regarding methane emission sources. However, to solve the problem of attributing methane emissions to sources on the ground, The Stanford Machine Learning Group similarly worked on a model that identified a different sector: oil and gas facilities. In their paper, *OGNet: Towards a Global Oil and Gas Infrastructure Database using Deep Learning on Remotely Sensed Imagery*, they detail their process of making a deep learning model that can detect oil and gas facilities based on aerial imagery [6]. The group used data from NAIP (National Agriculture Imagery Program), which captured the continental United States. They gathered 149 positive data points of satellite imagery with oil silos, and then systematically took coordinates from areas surrounding these oil and gas facilities, leaving them with 6,917 negative images.

They then developed a deep learning model, called OGNet, which was able to classify imagery for the presence of oil and gas facilities. Their model was pretty successful, with a precision score of 81% and a perfect recall score of 1.0 [6]. The OGNet research paper served as the main reference for building my model since I was trying to achieve a very similar goal, just with landfills instead.

Dataset

A significant challenge I encountered while making this model was the lack of available datasets to use for a landfill classification model. First, I needed a database of coordinates of different landfills throughout the continental United States, which was acquired through the LMOP database. Many of the coordinates led to inactive landfills or were not in the continental United States (i.e. Alaska, Hawaii, and Puerto Rico), which was an issue because NAIP only contains satellite imagery of the continental U.S. To combat this, I used Pandas to filter the unwanted coordinates from the data frame, leaving us with 1,286 usable coordinates.

Next, I used these coordinates to create an imagery dataset of positive images: images that contained landfills. I utilized NAIP imagery data from 2020-2022 through Google Earth Engine to create rectangular images that mostly contained landfills. A large part of creating the positive dataset was manual review because many of the pictures did not contain landfills in them. This was because many of the coordinates in the LMOP database were either not centered or just incorrect. After a secondary revision process, I was left with a total of 1,140 landfill images in our positive dataset.

Figure 1: Positive Images (Landfills)

The second part was creating the images for the negative dataset. To do this, a comprehensive set of coordinates containing small towns, cities, and rural areas were acquired from SimpleMaps and LatLong.net, and were fed into the same function that created the images for the positive dataset [7][8]. There were a total of 980 images in the negative dataset.

Figure 2: Negative Images (No Landfills)

This dataset has been uploaded to Kaggle for others to use for similar projects. It can be found in the references [9].

Methodology and Models

The two sets of images were then combined and split into train, test, and validation sets in an 80% to 10%, to 10% ratio. The imagery data was then resized to 200 x 256, augmented through horizontal and vertical flips, and normalized by finding the mean and standard deviation. Due to memory constraints, the images were also put into batches of 32 images for training. Using Pytorch and Timm, I imported and tested two State-Of-The-Art (SOTA) computer vision models, ResNet 50 and ResNet 34.

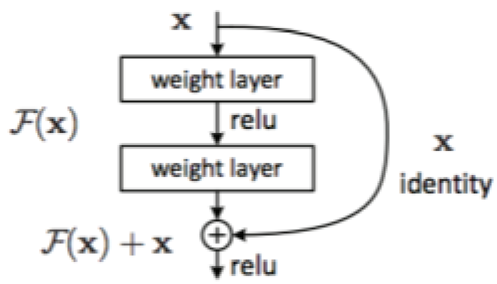

Figure 3: ResNet "Identity Shortcut Connection"

Modern computer vision models are made from deep learning neural networks that contain many layers. Each layer helps the computer learn about different features, like edges, shapes, and colors in a picture. However, increasing a network's depth is not as simple as stacking layers together. As a result of the vanishing gradient problem, the deeper a network goes, its performance becomes more saturated or even degrades [10].

ResNet is an artificial neural network that uses an "identity shortcut connection" that allows the model to skip one or more layers [5]. This allows the network to adjust new information without losing important details. Additionally, in a ResNet, the basic building blocks are residual blocks that contain two paths: the regular path where information flows through the layers, and the shortcut path, which allows information to skip over several layers. The information from both paths are combined, making it easier for the network to learn and remember important features [5][10].

For each model, I started by running 3 epochs using the pre-trained weights of the model. I then recorded and stored the weights of the model with the highest validation accuracy, and ran another 3–6 epochs using the weights of the new model. The learning rate was kept at a constant rate of 0.001 since smaller values degraded the model's performance.

Results

After experimenting with both ResNet 50 and ResNet 34, I found that RestNet 34 achieved a higher validation accuracy than ResNet 50 could. ResNet 50 capped at a validation accuracy of around 92%, whereas ResNet 34 was able to reach a validation accuracy of around 96%.

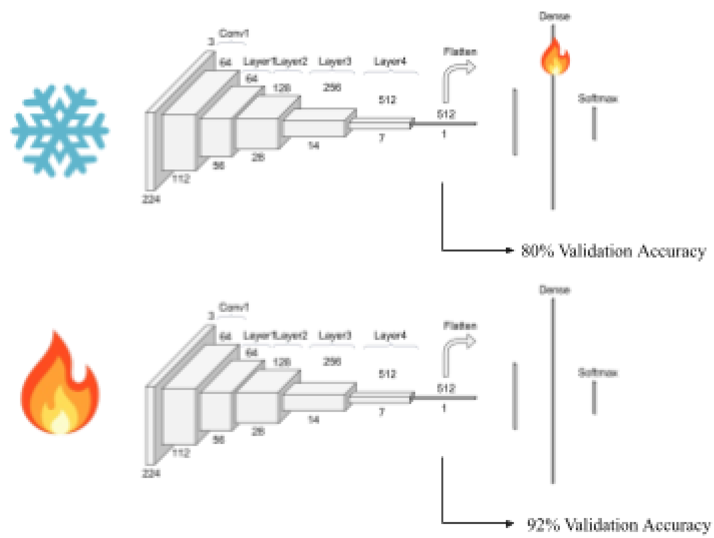

Figure 5: Freezing Versus Unfreezing Layers

Another factor that played a large role in training the model was freezing or unfreezing the layers (Figure 5). Freezing all the pre-trained layers except for the last one would be beneficial in reducing the amount of training time. However, freezing the layers degraded the model significantly, starting with a 10% between validation accuracy of frozen versus unfrozen and slowly decreasing as the training went on. Since the training time for a full model was not too long to begin with (~ 1 hour) and freezing significantly lowered the performance, I concluded that freezing had minimal benefits and was not worth it.

The model that worked best was trained by running 9 epochs using ResNet 34, and maintained a consistent learning rate of 0.001. The model achieved a training accuracy of 96.5%, and a validation accuracy of 96.14. The test accuracy of the model was 97.10%, and the model displayed a precision of 0.96 (96%). The recall and F-1 scores were 0.98 and 0.97 respectively.

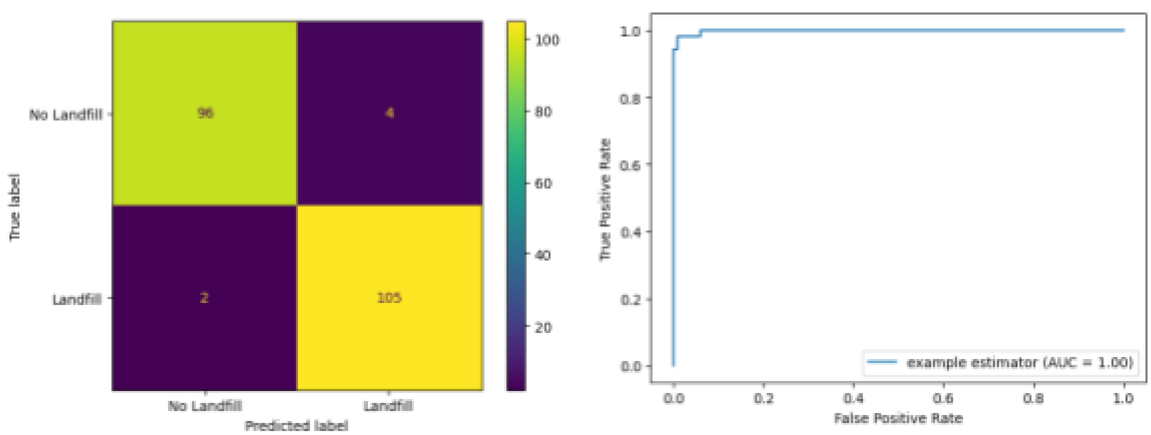

Figure 6: Confusion Matrix and ROC Curve

The confusion matrix and the ROC curve for the ResNet 34 model are shown above. The confusion matrix shows very low false positives and low false negatives, proving the model is well-performing. The ROC curve shows an almost perfect area under the curve, also showing the high accuracy of the model.

Conclusions

This research paper presented a model that streamlined the way we can identify landfills using satellite imagery. This work also presented an entirely new publicly available database that can be used for training future models with similar goals. The model performed with a very high accuracy of 97.1%, revealing that it has great potential for further improvements. The performance and accuracy of this model highlight its capability to continue an informed expansion of LMOP projects and uncover illegal landfills in the continental United States. This, in turn, can help combat the methane emissions released by landfill compositions, making a significant dent in methane's effects on global warming.

The successful results of this paper and the high accuracy of the model only pave the way for more experimentation. To take this research a step further, the model can be applied to a map of the continental United States to pinpoint the locations of landfill facilities. I could also modify the output to create a segmentation map or even the amount of methane a landfill emits. The model can also be tested with other forms of input, such as spectral imagery, to see if it can predict location and methane output. It would also be beneficial to explore more practical ways to create the datasets for this model, such as creating a dataset that involves less manual review (using the methods that OGNet did) or creating a worldwide dataset. Additionally, creating a deep learning model from scratch instead of using the pre-existing ResNet 34 could improve the model's performance.

The code for the CNN model can be found here:

https://github.com/anikaSeshan/LandfillNetResearch.git

The Kaggle dataset can be found here: Landfill Images Dataset - NAIP Imagery | Kaggle

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