

# GIS Deep Learning For Power Assets' Detection and Identification

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**Abstract**—In this study, ArcGIS Pro 2.8 identified power poles and towers from Light Detection And Ranging (LiDAR) point-cloud data. In previous research, machine learning has identified objects from such data. We sought to demonstrate a deep-learning model developed by the Environmental Systems Research Institute and a group based in Australia and whether deep learning is a viable solution for identifying power assets in three California areas. The deep-learning model was deployed in ArcGIS Pro using the Classify Point Cloud Using Trained Model geoprocessing tool. The model successfully identified some power poles in both rural and urban areas. A better training dataset might improve on this limited success, suggesting that deep learning can successfully classify point clouds. Those interested in using LiDAR point clouds with deep learning to classify power poles and towers should produce training data using accurately labeled data that accurately represents the objects of interest to ensure optimal results with a new model.

**Keywords**—LiDAR; deep learning; point cloud; ArcGIS Pro; point classification.

## I. INTRODUCTION

Light Detection And Ranging (LiDAR), a type of remote-sensing technology, uses pulsed lasers to measure variable distances, heights, or depths of objects and areas. LiDAR devices are generally mounted on Unmanned Aerial Vehicles (UAV). These UAVs are remotely operated to scan areas of interest. At a minimum, this process requires a two-person team to remotely operate the UAV and verify the data is correct [1]. This data can be input to software that can read the point-cloud data for further processing. UAVs and LiDAR data provide several benefits over sending people to physically inspect all assets of interest. For instance, a UAV can easily scan large areas without regard to the type of terrain (steep slopes, dense forests, etc.). Several studies have examined extracting objects from point-cloud data.

Based on the current and future potential of LiDAR data in assessing and managing forest structures, remote sensing and classification can identify specific trees in a cluster and more closely identify the species [2]. The article is relevant to our research question of whether LiDAR can be used to identify power poles and structures, which may be imbedded in forests or other rural areas.

3D LiDAR imaging could be used in conjunction with a Recurring Neural Networks (RNN) to identify different objects. With the progression of scanners, 3D LiDAR images provide enhanced measurement data [3]. The point spacing between objects could be leveraged to create a model to recognize objects [3]. The RNN model showed promise, and warrants further research, as does pursuing better 3D data.

Using Convolutional Neural Networks (CNNs), Maggiori et al. [4] created an end-to-end satellite-imagery classification framework, noting its ability to classify satellite images, identify objects, and produce quality images. Untrained models performed less well. From an existing model, they constructed a manually classified dataset with significant improvements. They propose a two-step approach with a small manually classified training dataset to classify a larger unclassified set.

Kudinov [5] used the Point Convolution Neural Network (PointCNN) framework to automatically identify power lines and poles. The group used artificial intelligence for the labor-intensive task of manually labeling the point cloud. Their study area was a city in Australia, and their dataset contained 540 million points. They trained their PointCNN model using four classes: other, wires, stray wires, and utility poles.

Studying the You Only Look Once (YOLO) deep-learning algorithm, Fan et al. [6] detect objects in point-cloud datasets for self-driving vehicles, which need real-time information to avoid collisions. Consequently, the researchers propose a computationally efficient algorithm, LS-R-YOLOv4, using color images and point-cloud data to precisely segment and detect objects. Borcs et al. [7] proposed a pipeline to quickly classify point clouds. One component of this pipeline is a CNN trained to classify objects.

LiDAR data can be used to accurately pinpoint large areas' micromorphology [8]. Comparing a Digital Elevation Model (DEM) generated from LiDAR data to the surveyed plots, Brubaker et al. [8] learned that their research was accurate to within 0.3–0.4 m of the actual survey, a single point in the point cloud. With their data, they generated the surface constraint of the surveyed area faster and from a greater distance compared to a traditional survey. The DEM is important as it allows LiDAR data to be accurately separated from ground, water, or any surface constraints based on elevation.

Azevedo et al. [9] showcased UAVs to replace helicopters. UAVs with LiDAR would help companies maintain their equipment more efficiently with a team of a few people for data vetting and to control the UAV. LiDAR data can be converted to point-cloud data and fed through an algorithm to help identify and sort items in the LiDAR data. They argue that, while the algorithm they used failed to correctly identify possible points, those points were classified as unidentified due to the difficulty of differentiating vegetation and other objects. They conclude that a more powerful algorithm may correctly identify points of interest and that Graphics Processing Units (GPUs) would process faster.

The CNN algorithm was able to transform, organize, and label data [10]. With orthophotos and LiDAR data, Nahhas et al. [10] created a digital surface model, DEM, shapes, and input other data through the model to detect buildings. From their findings and experiments, the CNN and machine-learning model accurately classified background and buildings and drew the geometry and shapes of the building from the LiDAR and orthophotos. They were able to transform low-level detail into highly detailed, classified features.

Section II describes the materials and methods used in the study. Section III presents the results and discusses the findings. Section IV concludes.

## II. MATERIALS AND METHODS

In this section, we define the problem, outline the data selection and acquisition, and lay out the methodology.

### A. Problem Definition

Utility companies must carefully manage their assets against various hazards, visually inspect their assets regularly. Generally, these assets require many hours to manage and are not easily accessible due to their remoteness. Dispatching teams of people to assess the status of power equipment is expensive and time consuming. LiDAR data serves as a cost-efficient alternative for surveying large areas of land and generating real-time images of objects.

The point-cloud data generated by scans can be analyzed to identify assets needing maintenance. Additionally, utility companies can lower labor and transportation costs as there is no need to send maintenance crews into the field.

The cost of LiDAR depends on the type of equipment and the range and scope of work [11]. LiDAR drones can potentially be cost effective for difficult-to-reach forested areas, rural towns, or high-elevation areas. LiDAR can also be used in high-density areas such as urban or suburban areas [12]. The high upfront cost leaves just maintenance of the equipment, future upgrades, and pilot licensing as needed [13]. These costs can be calculated in advance, while the ongoing costs of dispatching workers depends on the scope of work and may not be easily estimated [14]. In many cases, contractors may be required in difficult-to-reach areas and may not have the quality control utility companies need.

While manually assessing and inspecting equipment is beneficial as the information about them can be updated in real time, high-scale LiDAR data must be processed and analyzed to ensure error-free data [9][10].

LiDAR technology provides several benefits when surveying objects. Therefore, this study sought to answer the following question. Can utilities use LiDAR point-cloud data to accurately define asset locations (poles and towers)?

The literature suggests deep learning can be used to classify objects of interest. This study deployed a deep-learning model to classify points of interest (utility poles). In addition, we gauged the effectiveness of other ArcGIS Pro classification tools at classifying poles and towers. This study may be of interest to utility companies and individuals interested in using LiDAR to manage assets.

### B. Data Selection and Acquisition

Using publicly available point-cloud data from the United States Geological Survey website, we explored datasets from June 19, 2018, for parts of Santa Cruz, West Hollywood, and North Long Beach (>30 million points and 1.5 GB each) to study a PointCNN deep-learning model's ability to correctly classify power poles. The deep-learning model employed came from ArcGIS Online.

The following steps describe the point-cloud download process. (1) Navigate to the national US Geological Survey map [15]. (2) Select "Show where Lidar is available" and "Show AOI [Area Of Interest] Results" in the left pane. The latter may only show after an area of interest is defined. (3) Select the area of interest by Ctrl-clicking and dragging. (4) A results pane will appear on the right. Click "Lidar within AOI" for the download files. Note that all steps are for Windows users. Mac steps are similar.

### C. Methodology

This research explored ArcGIS geoprocessing tools, including a deep-learning model and additional tools. We classify the tools into three categories: (a) data conversion, (b) deep learning, and (c) .LAS conversion and discuss deploying a deep-learning model to classify point-cloud data.

#### 1. Data Conversion and Projection

The data files come from USGS in the .LAZ format. To use these files in ArcGIS Pro, they must be decompressed. The first step is to convert them to .LAS using the open-source laszip.exe executed at the command prompt: (1) Download the conversion tool [16]. Place the downloaded file in a folder with the .LAZ files. (2) Bring up the Command Prompt (Windows), allowing file access as necessary. (3) Type cd /d. (4) Copy the location of the .LAZ files from the file manager, paste it on the command line, and press Enter. (5) Copy the command **laszip.exe \*.laz** to the command prompt and press Enter. (Note: pressing Enter will start the tool converting the .LAZ files to .LAS files. The tool must be located in the same folder as the .LAZ files, otherwise it will not find them.) The converted files will appear in the folder with the .LAZ files.

ArcGIS Pro requires a .LAS dataset to manipulate the point-cloud data. In addition, the deep-learning model's documentation requires the point cloud's  $x$ ,  $y$ , and  $z$  coordinates be in metric. The USGS .LAS datasets, by default, are in imperial units. ArcGIS's "Create LAS Dataset" can perform this conversion: (1) Navigate to the Geoprocessing Tools pane in ArcGIS Pro and find "Create LAS Dataset." Click on the folder icon under Input Files and locate the .LAS files decompressed earlier. Under "Create PRJ For LAS Files," select "All LAS Files." (2) Click on the globe icon under Coordinate System. (3) A separate window will open for setting coordinate systems. Click on Current XY and find NAD 1983 NSRS2007 California (Teale) Albers (Meters) or whatever is appropriate for your dataset. It is found by expanding Projected Coordinate System – State Systems. (4) Click Current Z and navigate to "NAD 1983 (NSRS2007)" found by expanding Vertical Coordinate

System – Ellipsoidal-based – North America. Once the  $X$ ,  $Y$  and  $Z$  coordinates are correctly specified, click OK.

## 2. Deep-Learning Tools

Our main approach involved using a publicly available PointCNN deep-learning model to automatically classify power poles and towers. Due to resource and time constraints, this study instantiated an existing trained model to determine whether deep learning is an effective solution for extracting the desired objects from point-cloud data.

ArcGIS Pro provides three tools to classify data, train a model, and use a model: Prepare Point Cloud Training Data, Train Point Cloud Classification Model, and Classify Point Cloud Using Trained Model

This project employed the Classify Point Cloud Using Trained Model (CPCWTM) geoprocessing tool to run the trained model on the .LAS datasets. To run deep-learning models in ArcGIS, one must install the Deep Learning Framework for ArcGIS Pro 2.8. (1) Download and install required framework to run deep-learning models on ArcGIS [17]. At that link, click Deep Learning Libraries Installer for ArcGIS Pro 2.8 in the Download section. Unzip and run the executable. (2) Download the deep-learning model to classify power lines [18]. The tool is also on ArcGIS online through the ArcGIS Catalog Pane. You will need to store the deep-learning model in your project folder. (3) Open the CPCWTM geoprocessing tool. Enter your .LAS dataset under *Target Point Cloud*. Under Input Model Definition, locate the downloaded deep-learning model from the folder icon. Under *Existing Class Code Heading*, select Edit Selected Points. Under *Existing Class Codes*, select “1” to run the model on unclassified points. With all parameters entered, click Run. The required time to complete depends upon the size of the dataset and the computer’s resources. The model may take several hours to classify the point-cloud data. (4) Filter the layer to display only power poles: Select the .LAS dataset map layer in the Contents plane. On the Appearance tab of the ribbon click “LAS Data Points.” Turn off all but classification code 15—transmission tower—by unchecking the other checkboxes.

## 3. .LAS Classification Tools

We also evaluated whether ArcGIS’s .LAS classification tools in Geoprocessing Tools support classifying power poles and towers: “Classify LAS Ground,” “Classify LAS Building,” “Classify LAS by Height,” “Classify LAS Noise,” and “Change LAS Classification Codes.”

The point-cloud data was classified using the above tools prior to running the model without improvement. In addition, the “Classify LAS by Height” tool helped determine if poles could be classified by their height. The tool proved ineffective at classifying poles as it only considers the height of the point not its other attributes or its relation to neighboring points.

## III. RESULTS AND DISCUSSION OF FINDINGS

In this section, we present the results and discuss the findings.

## A. Results

The CPCWTM geoprocessing tool used with the PointCNN deep-learning model successfully classified point-cloud data points as power poles and towers. The model was able to identify power poles and towers in the Santa Cruz Mountains, West Hollywood, and Long Beach (Figures 1–3).

While the tools achieved the objective of identifying power poles and towers, they could have performed better. They performed better in urban areas than in rural areas, but it had difficulty finding most of the power poles and towers within the datasets examined. In the Santa Cruz dataset, only seven power poles were identified. In the North Long Beach dataset, several poles were identified but not in their entirety, and some poles were not classified at all. The West Hollywood dataset gave similar results. Further, the deep-learning model did not identify any power poles or towers in the densely forested parts of the Santa Cruz Mountains.



Figure 1. Scotts Valley, CA (Santa Cruz County).



Figure 2. North Long Beach, CA.



Figure 3. West Hollywood, CA.

The remote-sensing classification tools did not increase model performance compared to unclassified data. The model failed to identify many power poles and towers.

## B. Discussion of Findings

Our project produced several findings. Troubleshooting the .LAZ–LAS file conversion led us to discover a third-party tool for converting .LAZ files, discussed in an earlier section. Using the tool on the command prompt, our group converted multiple files at one time for greater efficiency.

The deep-learning model required the dataset’s projected coordinate system in the metric system. We used the “Classify LAS Dataset” geoprocessing tool to change the coordinate system. Some group members experienced issues

with plotting the data. More than once, the point cloud was plotted in the middle of the Atlantic Ocean. Each time this issue surfaced, team members repeated the first steps of the workflow. Importing newly converted data solved the problem each time, and the data was plotted correctly.

Running the CPCWTM geoprocessing tool resulted in key findings on converting data from imperial to metric measures. Finding a method to convert both the XY coordinates and the Z coordinates took a combined 20 hours. ArcGIS contains many coordinate systems with limited explanations of each system.

Using the PointCNN trained deep-learning model led us to several key findings. When running the model more than once, we found that ArcGIS occasionally did not always accept the parameters we entered. In one case, ArcGIS would not recognize where the downloaded tool was kept. Closing the project and creating a new one fixed the issue.

Another issue we faced was the inability to run the deep-learning model. Although the correct path to the deep-learning model was input from both the local file directory and ArcGIS Online, the CPCWTM tool could not find it. After several hours of troubleshooting, the issue was resolved by reinstalling ArcGIS pro on all desktop profiles.

The different members' varying computer hardware and processing capabilities was challenging. Recommended hardware for using ArcGIS Pro is a four-core central processing unit, with two cores at a minimum and 10 cores optimally. Devices with lower specifications had some issues, such as freezing and becoming unresponsive. The datasets in the research ranged from 1.5 to 3.2 gigabytes, and the group noticed that ArcGIS Pro to function with fewer issues with less data processed. Additionally, some troubleshooting was required for some users to get the machine-learning model to function. For example, ArcGIS Pro must be installed for all users or there will be an issue with permissions.

#### IV. CONCLUSIONS

Utilities must manage assets for reliable service and to protect property and life. Asset inspections are expensive, labor intensive, and difficult in hard-to-reach locations. LiDAR can efficiently scan areas and generate point-cloud data that can be efficiently and cost-effectively processed and classified to visualize objects of interest and identify physical changes with such software as ArcGIS Pro.

Small teams can quickly scan large areas and analyze the data to determine which assets need attention, focusing efforts on assets needing maintenance. This study validates deep-learning methods to classify power poles and towers from a LiDAR point cloud.

Due to time constraints and lack of training data, we opted for a model trained with other data. Though the study's results are suboptimal, they do show deep learning is viable. According to the Environmental Systems Research Institute's deep-learning documentation, a model developed with other data may underperform because the project data differs from the data used to train the model [19].

ArcGIS Pro comes equipped with tools to interactively classify points. These tools can be used to label points of

interest in the training and validation data that accurately represent the project data. These steps should produce a model that can automatically classify other point clouds [20].

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