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Managing power infrastructure using LiDAR

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ABSTRACT

This manuscript empirically focuses on machine learning to identify objects from point-cloud data. The literature suggests deep learning can be used as a tool to classify objects of interest. Researchers in this study used light detection and ranging (LiDAR) point-cloud data to identify power poles and towers. This study sought to demonstrate the use of a deep-learning model developed by a group based in Australia and ESRI to determine whether deep learning is a viable solution for identifying power assets in three California areas. 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. The deep-learning model successfully identified power poles in both rural and urban areas. However, the model performance was better in urban areas than in rural areas. This study supports the literature that deep learning can successfully classify point clouds. To improve the model performance and to ensure optimal results when training the model, the authors emphasize the importance of accurately labeled data to represent the objects of interest. To produce the desired results, one should develop one's own training and validation data.

1. 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 (NOAA, 2021). This data can be input into 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.

For instance, Van Leeuwen and Nieuwenhuis (2010) examined the current and future potential of leveraging LiDAR data to assess and manage forest structures, specifically how remote sensing and classification can identify specific trees in a cluster and more closely identify the species. The article is relevant to this research question because this study examines whether LiDAR can be used to identify power poles and structures, which may be embedded in forests or other rural areas. Van Leeuwen and Nieuwenhuis (2010) demonstrated that remote sensing techniques may help identify objects in a forest (in their case, individual trees). Power poles and towers may blend into a forest canopy and conclude that further research is needed to assess remote sensing and forest management, as well as using models to recognize point-cloud data points.

Prokhorov (2009) examined how 3D LiDAR imaging could be used in conjunction with a recurring neural network (RNN) to identify different objects. With the progression of scanners, 3D LiDAR images provide enhanced measurement data. Prokhorov (2009) investigated how the space of points between various objects could be leveraged to create a model to recognize objects. This research concluded that the RNN model showed promise and that further research into training RNN models is warranted, as is pursuing better 3D data.

Maggiori et al. (2016) created an end-to-end framework to classify satellite imagery using convolutional neural networks (CNNs). In their study, they observed how a CNN has significant

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capabilities in classifying satellite imagery data to identify objects and produce quality imagery. However, they also noticed that untrained models did not perform as well. They leveraged an existing model and constructed a set of manually classified data and saw significant improvement in the model. Therefore, they propose a two-step approach leveraging a small set of manually classified data to train a model to classify a large set of unclassified data.

Kudinov (2019), in collaboration with ESRI and AAM Group, 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 around 540 million points. They trained their PointCNN model using four classes: other, wires, stray wires, and utility poles to successfully identify power poles.

Fan et al. (2021) studied the You Only Look Once (YOLO) deep-learning algorithm to detect objects in point-cloud datasets. The focus of their research was object detection for self-driving vehicles. These vehicles need real-time information to make decisions and avoid collisions. Consequently, the researchers propose an alternate computationally efficient algorithm dubbed LS-R-YOLOv4 using color images and point-cloud data to precisely segment and detect objects. Borcs et al. (2017) proposed a pipeline that quickly classifies point clouds. One component of this pipeline is a CNN trained to classify objects. The model supports the identification of vehicles and pedestrians in urban settings.

Brubaker et al. (2013) showed that LiDAR data can be used to accurately pinpoint the micromorphology of a large area and compared their results to field-surveyed plots to determine their accuracy. They compared a digital elevation model (DEM) generated from LiDAR data to the surveyed plots. From their findings, they were able to learn that their research was accurate to within 0.3–0.4 m of the actual survey, which is accurate up to a single point in the point cloud. Their data allowed them to generate 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 the ground, water, or any surface constraints based on elevation.

Azevedo et al. (2019) showcased the use of UAVs to replace helicopters due to their risks and associated costs. The use of UAVs with LiDAR would help companies maintain their equipment at a lower cost over time, as it would only need a team of a few people to ensure that the data is correct and to control the UAV. The UAV is able to quickly scan a large area with the proper sensors and send data back to the controller. From there, the LiDAR data can be converted to point-cloud data and fed through an algorithm and software 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 between vegetation and other sources. Therefore, they conclude that a more powerful algorithm may correctly identify the points of interest and that graphics processing units (GPUs) can be used to increase the speed of processing the raw data.

Nahhas et al. (2018) proposed machine learning with LiDAR data and orthophotos. They showed that the CNN algorithm was able to transform, organize, and label the data. With the orthophotos and LiDAR data, they 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 up to a single data point and draw the geometry and shapes of the building from the LiDAR and orthophotos. Using this model, they were able to transform low-level detail into highly detailed, classified features.

2. Materials and methods

In this project, we test the ability of ArcGIS and the selected model to classify point clouds and reveal transmission-line assets from field-collected LiDAR data.

2.1. Problem definition

The Public Utility Commission requires utility companies, such as Pacific Gas and Electric and Southern California Edison, to carefully manage their assets due to recent wildfires such as the Camp, North Complex, and Carr fires. Senate Bill 901 (SB-901), passed in 2018, requires utility companies to have wildfire-mitigation plans. Utility companies are required to visually inspect their assets every 12–24 months of service and thoroughly inspect them every 3–5 years based on their type. Generally, these assets require many hours to manage and are not easily accessible due to their locations. 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 on the ground.

The point-cloud data generated by scans can be analyzed to identify assets in need of maintenance. In addition to the efficiency afforded by LiDAR, utility companies can potentially lower labor and transportation costs as there is no need to unnecessarily send maintenance crews into the field. The cost of LiDAR depends on the type of equipment to be purchased, as well as the range and scope of work (Antunes, 2018). LiDAR drones can potentially be cost-effective in difficult-to-reach forested areas, rural towns, or elevated areas. At the same time, LiDAR can be used in high-density areas such as urban or suburban areas (Singh et al., 2015). The high upfront cost leaves just maintenance of the equipment, future upgrades, and pilot licensing as needed (Van Tassel, 2021). These costs can be calculated in advance, while the ongoing costs of dispatching workers depend on the scope of work and may not be easily estimated due to fluctuating rates of pay (Glavinich, 2021). In many cases, contractors may need to be hired in areas that are difficult to reach and may not have the exact quality control utility companies need.

While manually assessing and inspecting equipment is beneficial as the information about them can be updated in real-time, LiDAR data must be processed and analyzed to ensure the data are error-free (Azevedo et al., 2019). A high-scale scan must be performed of target areas to produce error-free point-cloud data and these data must be processed to ensure assets are correctly identified (Nahhas et al., 2018).

LiDAR technology provides several benefits when surveying objects. Therefore, this study sought to answer the following question.

Can a utility company use LiDAR point-cloud data to accurately define asset locations (poles and towers)?

The literature suggests deep learning can be used as a tool to classify objects of interest. As a result, this study deployed a deep-learning model to determine its effectiveness in classifying points of interest. In addition, other ArcGIS Pro classification tools were employed to gauge their effectiveness at classifying poles and towers. This study may be of interest to utility companies and individuals interested in using LiDAR to manage assets.

2.2. Data selection and acquisition

This research project used publicly available point-cloud data from the United States Geological Survey website. Datasets from June 19, 2018, covering regions in Santa Cruz, West Hollywood, and North Long Beach were explored to determine the effectiveness of a PointCNN deep-learning model at correctly classifying power poles. The deep-learning model employed in this study was obtained from ArcGIS Online (see Methodology). Each dataset collected for this project contained at least 30 million points and the file sizes were at least 1.5 GB (Table 1).

Table 1: Point-cloud datasets

Region	File size	Points
North Long Beach	1.52 GB	54,586,808
Santa Cruz	3.20 GB	94,505,117
West Hollywood	1.57 GB	32,233,675

Step 1: Navigate to the national map on the USGS website: https://prd-tnm.s3.amazonaws.com /LidarExplorer/index.html.

Step 2: Select the "Show where Lidar is available" and "Show AOI Results" check boxes located in the left pane of the window (Fig. 1). Note that the "Show AOI Results" check box may only show up after an area of interest is defined as in Step 3.

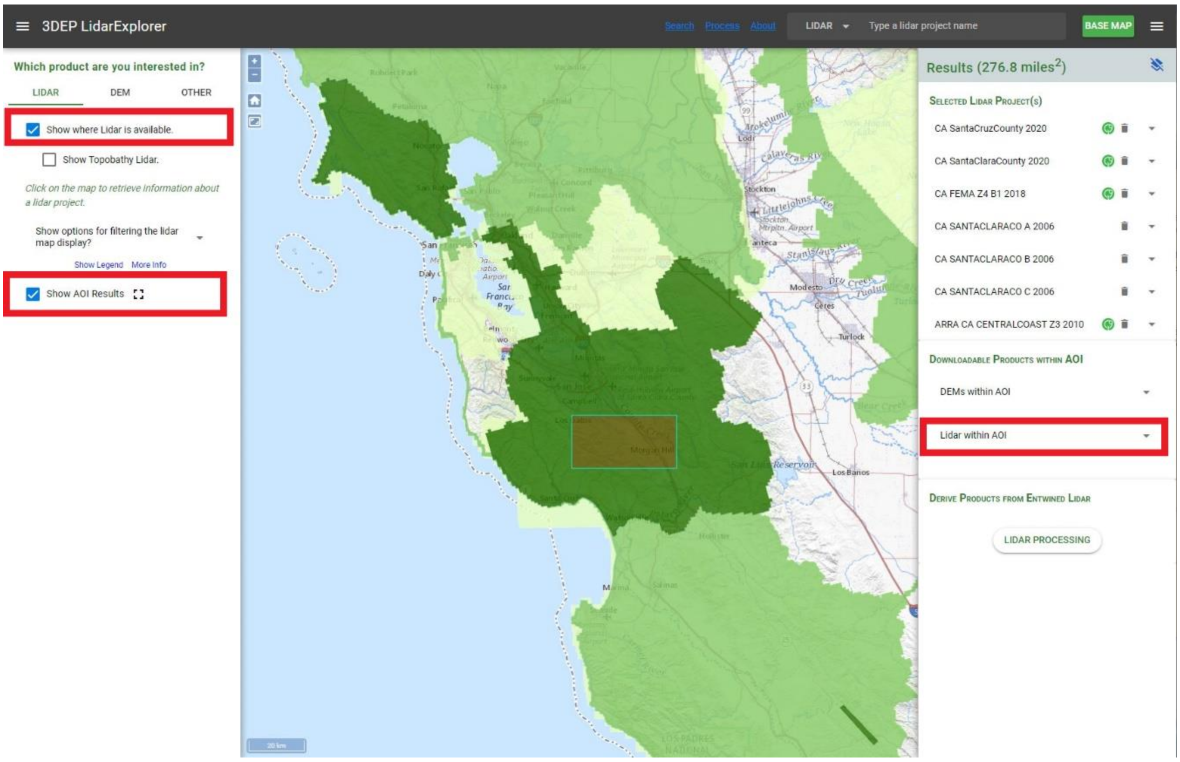


Fig. 1: USGS 3DEP LiDAR explorer

2.3. Methodology

This research study explored ArcGIS geoprocessing tools, including a deep-learning model, and additional tools that complement ArcGIS. This paper classifies the tools used into three categories: (a) data conversion, (b) deep learning, and (c) LAS conversion. This section discusses the process of deploying a deep-learning model to classify point-cloud data.

2.3.1. Data conversion and projection

The data files downloaded from USGS are compressed in the LAZ format. To use these files in ArcGIS Pro, the LAZ files must be decompressed. Therefore, the first step in the workflow is to convert the LAZ files to LAS using the open-source application laszip.exe. The program can be executed using the command prompt (as done in this study) or a graphical user interface. The steps below show the process.

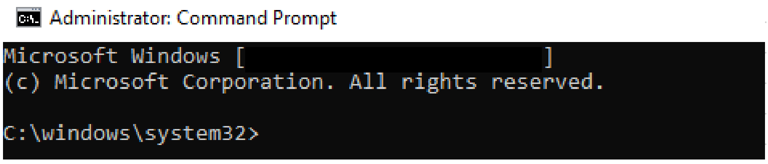
Step 1: Download the conversion tool from http://lastools.org/download/laszip.exe. Place the downloaded file tool in the folder where your LAZ files are located.

Step 2: Search for the Command Prompt in the search menu, then press CRTL + Shift + Enter. The computer will ask if you would like to allow the application to make changes to your computer. Select YES.

Step 3: In the Command Prompt, type cd/d ("Before" and "After" photos are included in Fig. 2 clarification on how to perform Steps 3–5)

Step 4: Copy the location of the LAZ files from the computer and enter it in the command prompt. Click on the dropdown arrow to copy the location address. Once the file location is entered into the command prompt, press Enter on your keyboard (Figs. 3 and 4).

Before:



After:

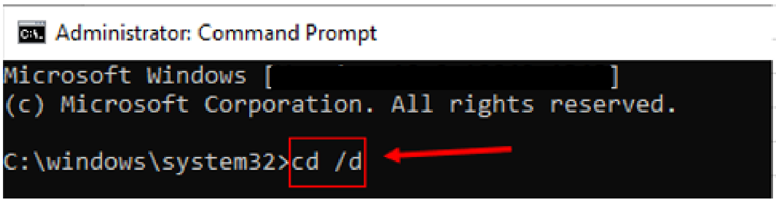


Fig. 2: Before and after screenshots for step 3

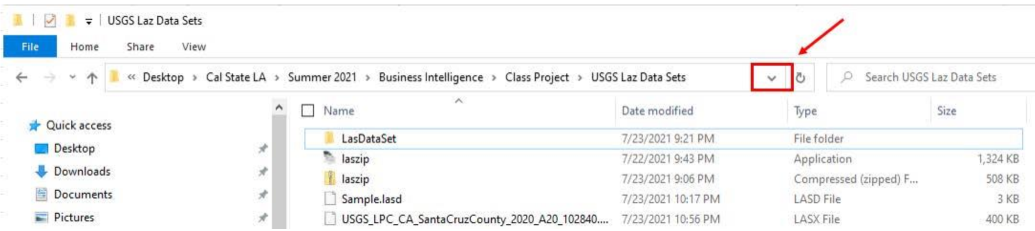


Fig. 3: Executing laszip.exe via command prompt

Before:

After:

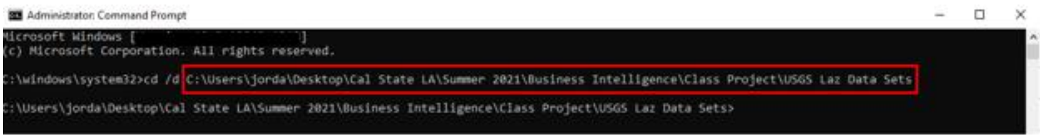
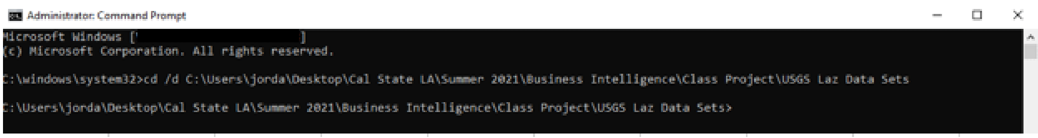


Fig. 4: Before and after screenshots for step 4

Step 5: Copy the following command to the command line: laszip.exe *.laz (Fig. 5) and press Enter on your keyboard (Note: pressing Enter will initiate the tool to begin converting the LAZ files to LAS files. However, the tool must be located in the same folder as the LAZ files, otherwise, the tool will not find them).

Before:



After:

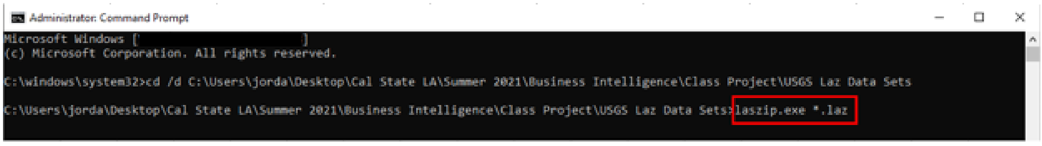


Fig. 5: Before and after screenshots for step 5

The converted files will appear in the same folder as 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 to be based on the metric system. For these reasons, the second main step in the conversion process uses the Create LAS Dataset tool found in ArcGIS. The LAS data sets retrieved from the USGS website, by default, are in imperial units. The following steps and Figs. 6, 7, and 8 show how to create a LAS data set and convert the units of measurement to meters using the Create LAS Dataset tool.

Step 1: Navigate to the Geoprocessing Tools pane in ArcGIS Pro and search for Create LAS Dataset. Then 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 (Fig. 6).

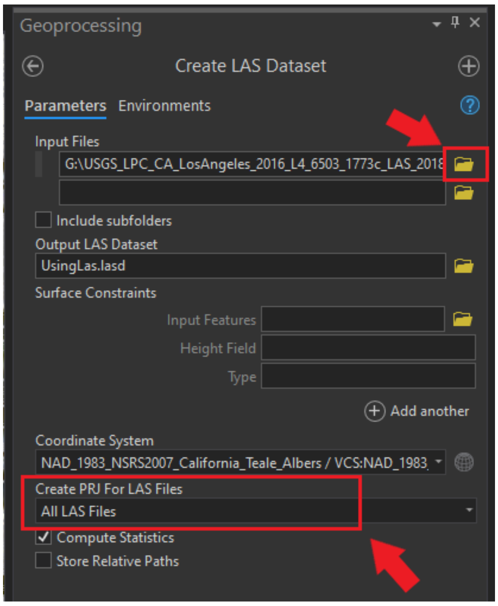


Fig. 6: Create LAS dataset geoprocessing tool

Step 2: Click on the globe icon under Coordinate System (Fig. 7).

Step 3: A separate window will open where coordinate systems can be changed. Click on Current XY and navigate to the NAD 1983 NSRS2007 California (Teale) Albers (Meters) or whatever is appropriate for your dataset. It is found by expanding Projected Coordinate System–State Systems (Fig. 8).

Step 4: Click Current Z and navigate to NAD 1983 (NSRS2007). It can be found by expanding Vertical Coordinate System–Ellipsoidal-based–North America. Once the *XY* and *Z* coordinates are correctly specified, click OK (Fig. 8).

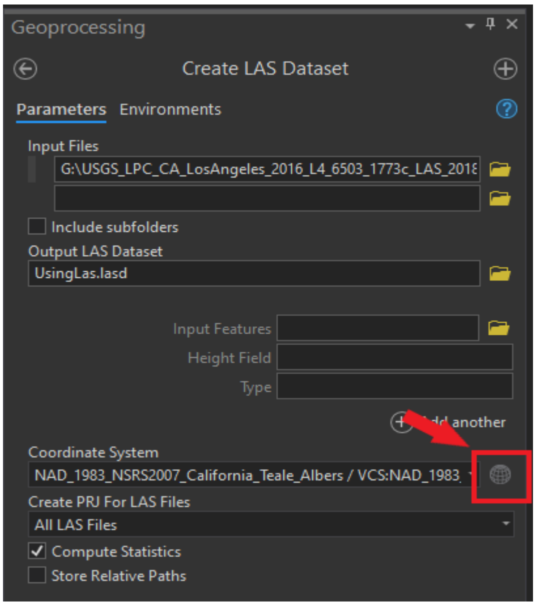


Fig. 7: Changing the projected coordinate system

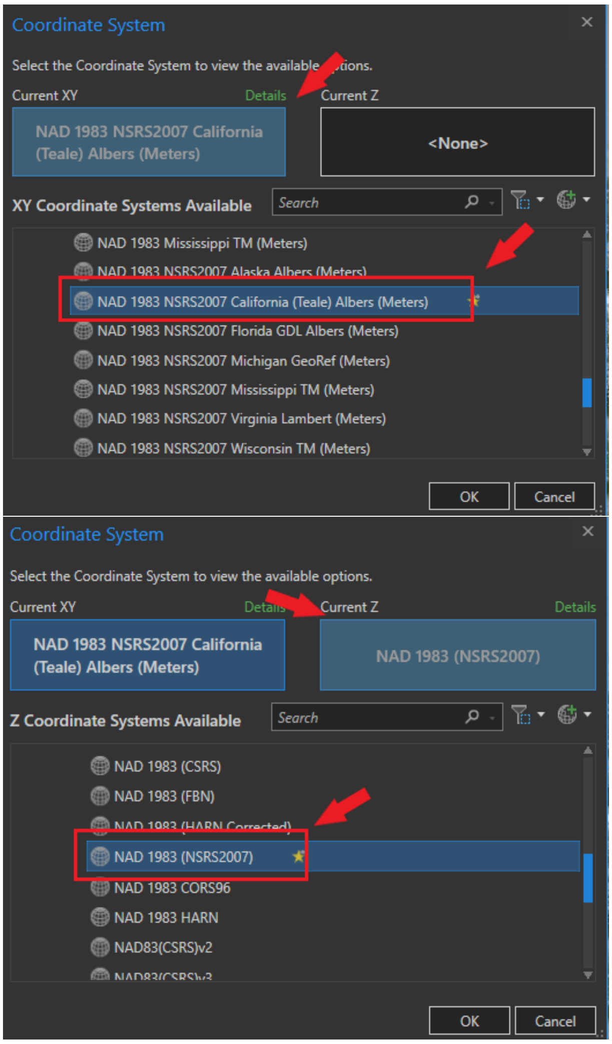


Fig. 8: Changing the projected coordinate system

2.3.2. Deep-learning tools

This study's 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
- 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 ensure the Deep Learning Framework for ArcGIS Pro 2.8 is installed. Once the LAS dataset has been created, the following steps can be followed to install the deep-learning framework and deploy the deep-learning model.

Step 1: Download and install the required framework to run deep-learning models on ArcGIS (GitHub.com). On the provided link, you will need to click on the Deep Learning Libraries Installer for ArcGIS Pro 2.8 link to begin the download process. The link is located under the Download section. You will need to unzip the downloaded file before running the executable located in the downloaded folder. Then you simply follow the download wizard instructions to install the framework.

Step 2: Download the deep-learning model to classify power lines, (ArcGIS.com). You can also find the tool on ArcGIS online, accessible through the ArcGIS Catalog Pane. You will need to store the deep-learning model in your project folder.

Step 3: Open the CPCWTM geoprocessing tool. Enter your LAS data set under Target Point Cloud. Under Input Model Definition, locate the deep-learning model to classify power lines by clicking on the folder icon and retrieving the file. Under Existing Class Code Heading, select Edit Selected Points. Under Existing Class Codes, select "1" to run the model on unclassified points. After all parameters have been entered, click Run (Fig. 9). The required time to complete depends upon the size of the data set and the computer's resources. The model may take several hours to classify the point-cloud data.

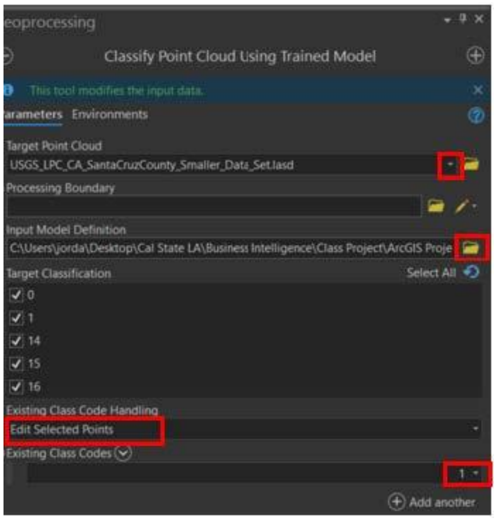


Fig. 9: Classify point cloud using the trained model tool

Step 4: Filter the layer to display only power poles: Click on the LAS data set map layer located in the Contents plane to ensure it is selected. On the ribbon, click the Appearance tab. Then click on the LAS Data Points button. Turn off all other codes besides classification code 15—transmission tower—by unchecking the corresponding checkboxes (Fig. 10).

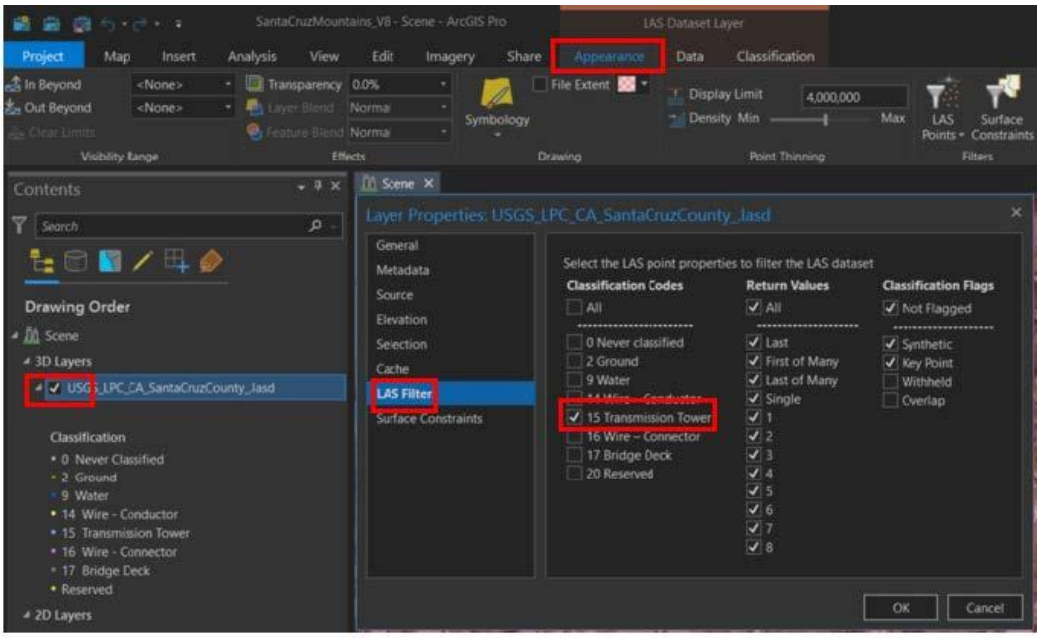


Fig. 10: Filter LAS dataset

Once you click OK, the map will update to include only points classified as transmission towers.

2.3.3. LAS classification tools

This research study also explored the ArcGIS LAS classification tools to evaluate whether these tools will support the classification of power poles and towers. The following LAS classification tools were explored and can be found in the geoprocessing-tools pane.

- Classify LAS Ground
- Classify LAS Building
- Classify LAS by Height
- Classify LAS Noise
- Change LAS Classification Codes

The point-cloud data were classified using the mentioned tools prior to running the model and these tools did not improve the performance of the PointCNN deep-learning model. In addition, the Classify LAS by Height tool helped determine if poles could be classified by their height. The tool did not prove effective at classifying poles as it only considers the height of the point, not its other attributes or its relation to neighboring points.

3. Results and findings

3.1. Results

The CPCWTM geoprocessing tool in conjunction 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. Results of these areas are shown in Figs. 11, 12, and 13.

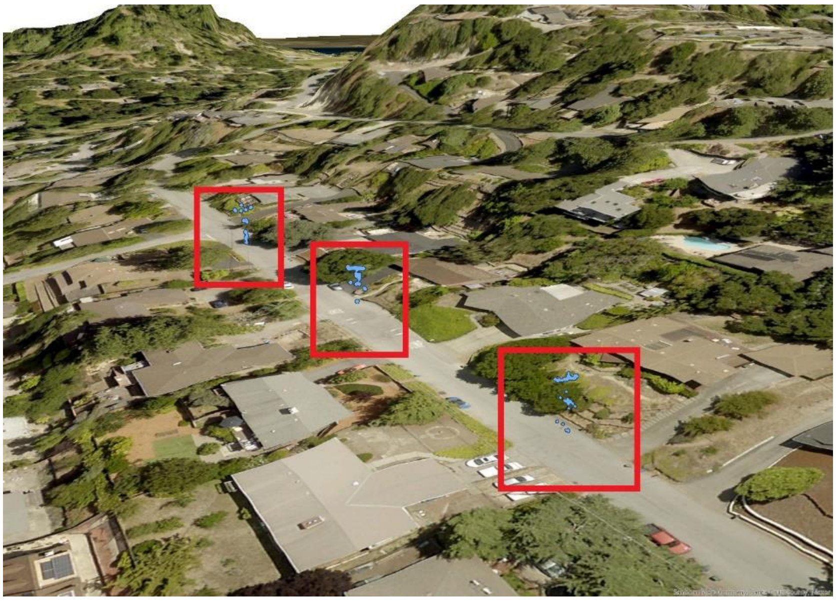


Fig. 11: Scotts Valley, CA (Santa Cruz County)

Fig. 12: North Long Beach, CA

While the tools technically achieved the objective of identifying power poles and towers, the performance could have been better. The tool performed better in urban areas than in rural areas, but it had difficulty finding most of the power poles and towers within the data sets examined. In the Santa Cruz data set, 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. Similar results were experienced in the West Hollywood dataset. Further, the deep-learning model did not identify any power poles or towers in the densely forested parts of the Santa Cruz Mountains.

The remote-sensing classification tools did not result in increased performance of the model compared to unclassified data. With both increased classification intensity and unclassified data, the model produced similar results. It failed to identify a large majority of power poles and towers in the area. The model's overall results were underwhelming.

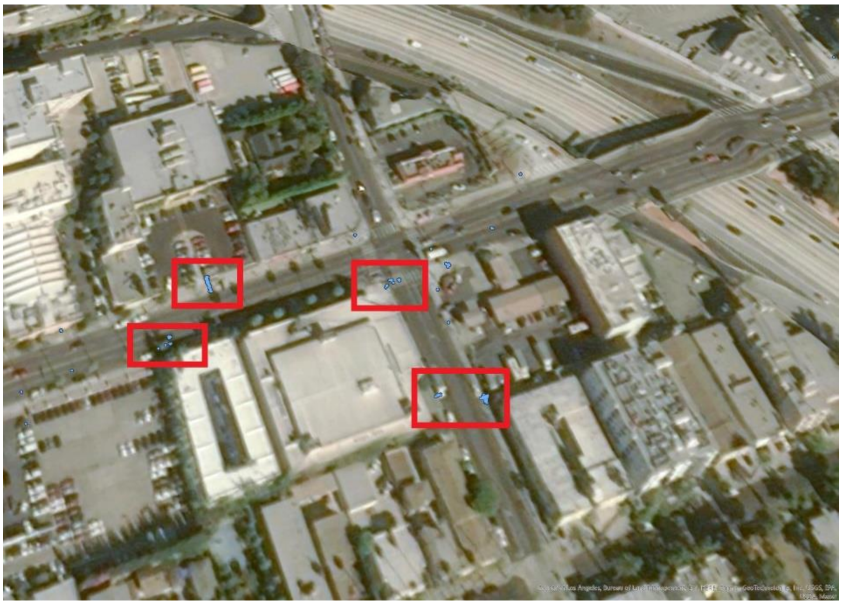


Fig. 13: West Hollywood, CA

This section may be divided into subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

3.2. Discussion of findings

Based on our research and efforts to convert LAZ files to LAS files and use the CPCWTM geoprocessing tool in conjunction with the PointCNN deep-learning model, our project produced several findings.

Troubleshooting the LAZ-to-LAS file conversion led us to discover a third-party tool for converting LAZ files. The third-party tool, discussed in an earlier section, was essential for this research. After the download, we found that one must place the downloaded tool in the folder containing the LAZ files. Otherwise, the command prompt would not be able to automate the process. Using the tool and the command prompt allowed our group to convert multiple files at one time for greater efficiency. One group member tried the graphical user interface bundled with the third-party tool in lieu of the command prompt. When doing so, the tool can be saved outside of the folder where the LAZ files are stored.

The deep-learning model required the dataset's projected coordinate system to be based on 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 (i.e., converting LAZ to LAS files and importing a "fresh" set of converted LAS files). 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 how to convert data from feet to meters. We found that the data must be converted to meters for the PointCNN deep-learning tool to run as intended, based on the documentation provided by the group who developed the tool. As such, our group had to learn to convert the data from feet to meters. 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. We successfully converted the data to meters using NAD 1983 NSRS2007 California (Teale) Albers (Meters) and NAD 1983 (NSRS2007) for the XY and Z coordinates, respectively. See Data Conversion Tools for more information on our findings and their implementation.

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 experienced glitches and other issues accepting the parameters we entered (Fig. 14). In one case, ArcGIS would not recognize where the downloaded tool was kept. Closing the project and creating a new project scene fixed the issue.

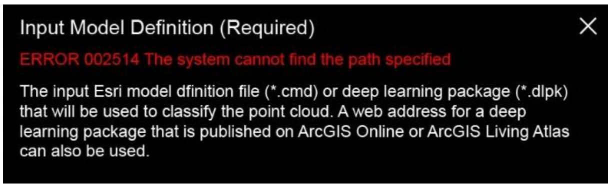


Fig. 14: Error message

Another issue faced by one member of the group was the inability to run the deep-learning model using a Windows operating system. The CPCWTM tool requires the location of the deep-learning model as one of its input parameters. When the correct path was input from both the local file directory and ArcGIS Online, the tool produced an error indicating that the system could not find the path. After several hours of troubleshooting, the issue was resolved by uninstalling ArcGIS pro and reinstalling it on all desktop profiles.

Varying levels of computer hardware and processing capabilities among the different members of the research group were a challenge that the group had to overcome. Recommended hardware for using ArcGIS Pro is a four-core CPU, with two cores at a minimum and 10 cores for optimal results. Devices with lower specifications had some issues, such as freezing and becoming unresponsive. The file sizes of the datasets used in the research ranged from 1.5 to 3.2 gigabytes, and the group noticed that lowering the amount of data processed allowed ArcGIS Pro to function with fewer issues. 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. The differences in computing power and file sizes were a challenge that the group had to overcome due to the project's deadline.

3.3. Discussion and next steps

Utility companies must manage their assets to provide reliable service, but also to prevent property-and life-threatening events. The process of inspecting power assets is labor intensive, carries high financial costs, and is difficult to implement due to hard-to-reach locations. LiDAR is a remote sensing technology that offers teams the ability to efficiently scan surface areas and generate point-cloud data. These data can be efficiently and cost-effectively processed and classified to visualize objects of interest using software such as ArcGIS Pro.

A small team can use a UAV to quickly scan large areas and then analyze the data to determine which assets need attention, thus focusing efforts on assets in need of maintenance. This study sought to determine if a LiDAR point cloud can be used to locate power poles and towers. The literature showed the successful application of deep learning to correctly classify these objects. As a result, this study pursued the use of a deep-learning model to validate whether this was a viable method.

The model employed was developed by ESRI in collaboration with a group based in Australia. Due to time constraints and lack of training data, the group opted for a model trained by someone else. Although the results garnered in this study were not optimal, they do show that deep learning is a viable method. According to ESRI's deep-learning documentation, a model developed by someone else may not perform as intended due to differences in the project data and the data used to train the model in such attributes as point spacing, intensity, and the number of returns (Esri, 2021a).

Therefore, to produce the desired results, one should develop one's own training and validation data. 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. These data should be an accurate representation of the objects of interest. Then, a model should be trained using the developed training and validation data. These steps should produce a model that can be deployed to automatically classify other point-cloud datasets (Esri, 2021b).

4. Conclusion

This manuscript empirically focuses on machine learning to identify objects from point-cloud data. The literature suggests deep learning can be used as a tool to classify objects of interest. This study sought to demonstrate the use of a deep-learning model to determine whether deep learning is a viable solution for identifying power assets in three California areas. 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. The deep-learning model successfully identified power poles in both rural and urban areas. However, the model performance was better in urban areas than in rural areas. This study supports the literature that deep learning can successfully classify point clouds.

Acknowledgment

The group would like to acknowledge Professor Vivian Sultan and Teacher Assistant Benjamin Pezzillo for their guidance and contribution to the group research project. Their support (both technical and personal) was a significant factor in our group's success. On behalf of the group, thank you for your continued support and effort to see this project through to the end. This research is based on students' course project work at the graduate school, Information Systems department of California State University, Los Angeles. This research received no external funding. This research project used publicly available point-cloud data from the United States

Geological Survey website https://prd-tnm.s3.amazonaws.com/LidarExplorer/index.html#/. Point cloud data covering regions in Santa Cruz, West Hollywood, and North Long Beach were downloaded and analyzed.

Compliance with ethical standards

Conflict of interest

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