LiDAR Data Processing for Utility Asset Management and Fire Risk Assessment

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***Abstract*—California requires utility companies to implement wildfire-mitigation plans to prevent and reduce the risk of catastrophic fires. Manually tracking and evaluating widely distributed equipment, often in very rural and rough terrain, is expensive and labor intensive. This paper demonstrates proof of concept for a light detection and ranging (LiDAR) point-cloud data-processing tool and explores the potential benefits associated with such a tool. LiDAR is widely used for various applications, including mass asset surveys, vegetation management, and structural-load analysis. The authors explored various ArcGIS geoprocessing tools as part of this study. In summary, this paper provides valuable insights into using ArcGIS tools for LiDAR processing and highlights the potential benefits of accurate geolocation data extraction from LiDAR point clouds within utility service territories.**

Keywords- LiDAR Data Processing; Utility Asset Management; Fire Risk Assessment; ArcGIS Tools.

I. INTRODUCTION

Light detection and ranging (LiDAR) can offer potential benefits to California utilities struggling to reduce the cost of tracking their widely distributed assets.

A. *Problem Statement*

In 2018, California enacted Senate Bill 901 requiring utility companies to implement wildfire-mitigation plans to prevent and reduce the risk of catastrophic fires caused by their equipment. As part of these plans, utility companies must conduct regular visual inspections of their assets, such as power lines, poles, transformers, and substations, according to their type and rate of service. These inspections range from 12 to 24 months for routine maintenance, to 3 to 5 years for comprehensive examination. However, inspecting these assets is not an easy task, as they are often located in remote and rugged areas, where access is limited, and terrain is challenging. Sending crews of inspectors to these locations is time consuming and costly and may not capture all the relevant information needed to assess the condition and performance of the assets.

To overcome these challenges, utility companies use LiDAR technology, which uses laser pulses to measure the location and reflectivity of objects in three dimensions. LiDAR can capture high-resolution point-cloud data of the utility assets and their surroundings, which can be used by utility companies to identify, locate, and monitor their assets more accurately and more efficiently. However, processing and analyzing LiDAR data is not a trivial task; it requires specialized software and expertise. Many utility companies currently outsource this task to third-party vendors, which adds to their expenses and reduces their control over data quality and security.

To address this issue, utility companies can benefit from developing their own LiDAR data-processing tools, which would allow them to bring the processing in-house and save on vendor fees. A LiDAR data-processing tool would help utility companies automate the extraction and classification of assets from point-cloud data and improve their geolocation accuracy and reliability. This would result in better wildfire-mitigation plans, as utility companies would have more up-to-date and detailed information on their assets and their potential fire hazards.

B. *Objectives*

This paper demonstrates a proof of concept for a LiDAR data-processing tool that would allow utility companies to process and analyze their own LiDAR point-cloud data. The paper also investigates the potential benefits of this tool for improving utility asset management and fire-risk assessment.

Utility companies use LiDAR for various purposes:

- Mass asset surveys: LiDAR can help identify the components and configurations of each pole in the service territory, such as wires, cross-arms, insulators, and transformers.
- Vegetation management: LiDAR can help survey the trees and vegetation that may infringe on the distribution lines and pose a fire hazard or a reliability issue.
- Structural load analysis: LiDAR can help determine the number and condition of poles in high-fire-risk areas and help assess their structural integrity and load capacity.

Utility companies are constantly improving the quality of their asset data by identifying and resolving data-quality issues, such as missing, inaccurate, or outdated information. They are also working on forecasting fire hazards using data-driven models and methods to estimate the probability and severity of fires caused by their equipment.

LiDAR offers the opportunity to extract more accurate geolocation data for utility assets, which can enhance the quality and reliability of the asset data and improve the accuracy and efficiency of the fire-hazard models.

This paper offers a first use case in studying the potential benefits of developing a LiDAR data-processing tool for utility companies. The paper will also evaluate the feasibility and scalability of the tool and identify the challenges and opportunities for future development.

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II. Background and Overview of LiDAR Data Processing Tools

LiDAR, a remote-sensing technology, uses pulsed lasers to measure and record distances, heights, and depths of objects and areas. It accurately, precisely, and flexibly examines natural and artificial environments. LiDAR data are collected aerially or terrestrially using an unmanned aerial vehicle (UAVs) or unmanned ground vehicles (UGVs). Technicians remotely operate UAVs to scan areas of interest from altitudes greater than ten meters. At a minimum, this process requires a two-person team to remotely operate the UAV and verify the data is correct [1]. Software can read these point-cloud data for further processing. In contrast, UGVs' detection distances range below ten meters to perform precise geometric measurements. 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 terrain (steep slopes, dense forests, etc.).

Several studies have examined the extraction of objects from point-cloud data. For instance, Van Leeuwen and Nieuwenhuis [2] examined the current and future potential for leveraging LiDAR data to assess and manage forest structures, specifically how remote sensing and classification can identify specific trees in clusters and more closely identify species. The article is relevant to this use case because this study examines whether LiDAR can be used to identify power poles and structures, which may be imbedded in forests or other rural areas. Van Leeuwen and Nieuwenhuis demonstrate that remote sensing techniques may help identify objects in a forest (in their case, individual trees) and conclude that further research is needed to assess remote sensing and forest management, as well as using models to recognize objects within point-cloud data [2]. Power poles and towers may blend into a forest canopy, as do to individual trees.

In 2009, Prokhorov [3] 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 [3]. Prokhorov investigated how the space of points between various objects could be leveraged to create a model to recognize objects [3]. 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. [4] 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 advantages when 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 [5], working 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. [6] 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 alternative computationally efficient algorithm dubbed LS-R-YOLOv4 using color images and point-cloud data to precisely segment and detect objects. Borcs et al. [7] 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. [8] showed that LiDAR data can be used to accurately pinpoint 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. Their research model was accurate to within 0.3–0.4 m based on manual surveys, 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 into ground, water, and any surface constraints based on elevation.

Azevedo et al. [9] showcased the use of UAVs to replace helicopters to reduce risks and associated costs. UAVs and LiDAR have lower equipment costs over time, as a team of just a few people can ensure that the data is correct and control the UAV. Equipped with the proper sensors, the UAV is able to quickly scan a large area 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 objects. They conclude that a more powerful algorithm may correctly identify the points of interest and that graphics processing units can be used to reduce the time required to process the raw data.

Nahhas et al. [10] 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, and shapes. They also input other data 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 drew 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.

Sultan et al. [11] empirically focused on machine learning to identify power poles and towers from point-cloud data. This study sought to demonstrate the use of a deep-learning model developed by Azevedo et al. [9] 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 desired objects from point-cloud data. The deep-learning model successfully identified power poles in both rural and urban areas. Although 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 suggest more accurately labeled data representing the objects of interest.

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 by not sending maintenance crews into the field unnecessarily. The cost of LiDAR depends on the type of equipment purchased and the range and scope of work [12]. LiDAR drones can potentially be cost effective in difficult-to-reach forested areas, rural towns, or high elevations. LiDAR can also be used in densely populated areas such as urban or suburban areas [13]. The high upfront cost leaves just maintenance of the equipment, future upgrades, and pilot licensing as needed [14]. 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 [15]. 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. On the other hand, manually assessing and inspecting equipment is beneficial as the information about them can be updated in real time, whereas LiDAR data must be processed and analyzed to ensure the data are error free [9]. 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 [10]. LiDAR technology provides several benefits when surveying objects. Therefore, this study sought to answer the following question. Can a utility company process LiDAR point-cloud data to accurately define asset locations?

The literature suggests deep learning can be used to classify objects of interest. Therefore, this study will instantiate the deep-learning model deployed by Sultan et al. [11] to determine its effectiveness at processing sample point-cloud data. In addition, other ArcGIS Pro classification tools will be studied and tested to gauge their effectiveness at classifying poles and towers. This study may be of interest to executive teams of utility companies, as it can help them decide whether to bring the LiDAR data-processing in-house and the potential benefits of doing so. For example, by processing and analyzing their own LiDAR data, utility companies may be able to improve the accuracy of their asset location data, which can enhance their asset management and fire-risk assessments.

III. METHODOLOGY

For this project, the authors will explore ArcGIS geoprocessing tools, including the deep-learning model deployed, image analytics, and additional tools that complement ArcGIS. Sultan et al. [11] classifies the tools used into three categories: (a) data conversion, (b) deep learning, and (c) LiDAR Aerial Survey (LAS) conversion.

ArcGIS Pro software from the Environmental Systems Research Institute (ESRI) provides three tools to classify data, train a model, and use a model for point-cloud data classification. The following ArcGIS Pro classification tools will be explored and tested by the project team:

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

Phase 1 of this project will include exploration of the tools to evaluate whether ArcGIS Pro LAS-classification tools will support the classification of power poles and towers. A preliminary recommendation should follow Phase 1. Given a positive recommendation, Phase 2 of the project may start to train the model on some sample point-cloud data to give it the best chance of correctly identifying buildings and electrical-system assets in the service territory.

- **Goal:** Classify LiDAR points as wire conductors, transmission towers, and high vegetation.
- **Software:** ArcGIS Pro 3.1.2 with Advanced functionality *(e.g. 3D Analyst Tools)* and ArcGIS Pro 3.1 Deep Learning Frameworks.

A. System Preparation

To prepare a conventional personal computer to run ArcGIS Pro and the other software used in this work, update the computer system and software with the latest versions and drivers. After updating ArcGIS Pro to version 3.1.2 or higher, install the Deep Learning Library downloaded from the ESRI website.

B. Data Preparation

1) Training the Classification Model

Preparation work not covered in this guide involved the classification model and training dataset. Training data were validated, and a classification model was trained using the validated training data.

That work was done using the step-by-step instructions in “Learn ArcGIS tutorial” [16] with some modifications for Classes 05, 14, and 15, and the maximum number of epochs (50) was set in the Train Point Cloud Classification Model

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tool in “Train point cloud classification model” [17] and “Classify powerlines from lidar point clouds” [18]:

The LAS dataset had to be converted into smaller training blocks using the Prepare Point Cloud Training Data geoprocessing tool in ArcGIS Pro. Ground (Class 2) and noise (Class 7) points were excluded from the training data. As Ground points typically account for a large portion of the total points, excluding ground points made the training process quicker. Block Size and Block Point limits were determined by the training and validation dataset.

Next, the Train Point Cloud Classification Model geoprocessing tool was used to train a model for classification. The focus of the model training was on three specific classes:

- 05 – High Vegetation
- 14 – Wire Conductor
- 15 – Transmission Tower

That meant in addition to 14 – Wire Conductor, the settings were adjusted in Class Remapping to include the those shown in Fig. 1. Those determinations were made after reviewing the diversity of classes in the point cloud data in the Layer Properties (Fig. 2).

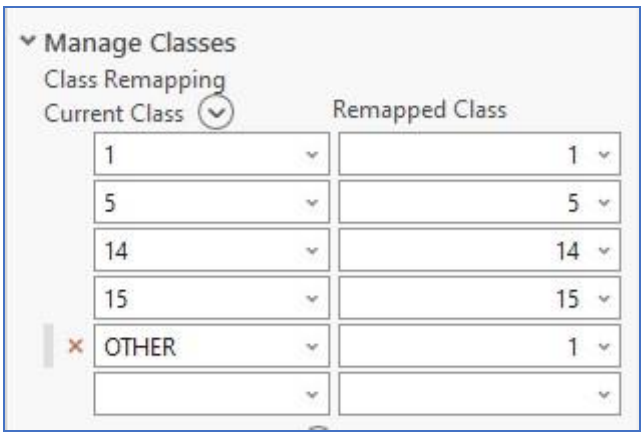


Figure 1. Class remapping settings.

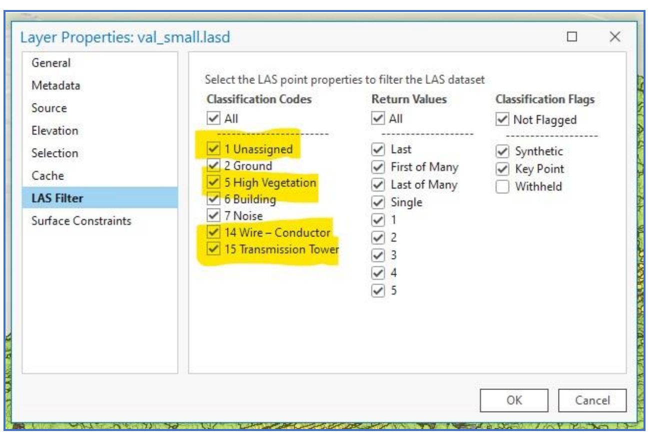


Figure 2. Layer properties dialogue.

Existing 01 – Unassigned were remapped as unassigned. Since 02 – Ground and 07 – Noise were excluded from the training data in an earlier step, they are subsequently ignored in this model**.** Any points classified as 06 – Building are remapped as “OTHER” into 01 – Unassigned.

The validated training data (Fig. 3) depicts 14 – Wire Conductor in yellow, 15 – Transmission Tower in blue, and 05 – High Vegetation in green. Data classified as 07 – Noise appears in red, 02 – Ground appears as brown, and 01 – Unassigned as gray. A fully rendered detail image (Fig. 4) shows 14 – Wire Conductor (yellow) among areas where 05 – High Vegetation is taller than the transmission lines.

Training Loss and Validation Loss values (Figs. 5, 6, and 7) generally decreased, indicating the model learned from the process. After 50 epochs, the highest recall is over .93.

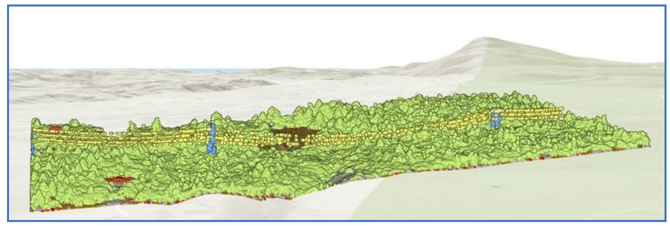


Figure 3. Validated training data.

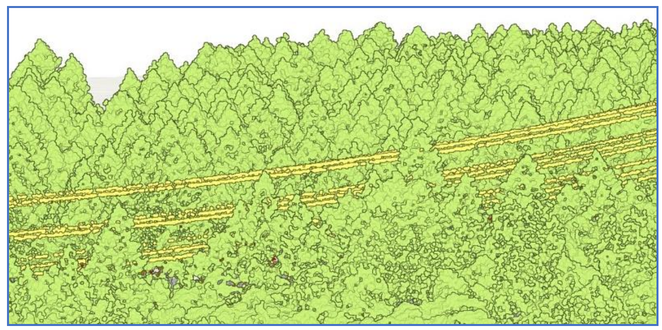
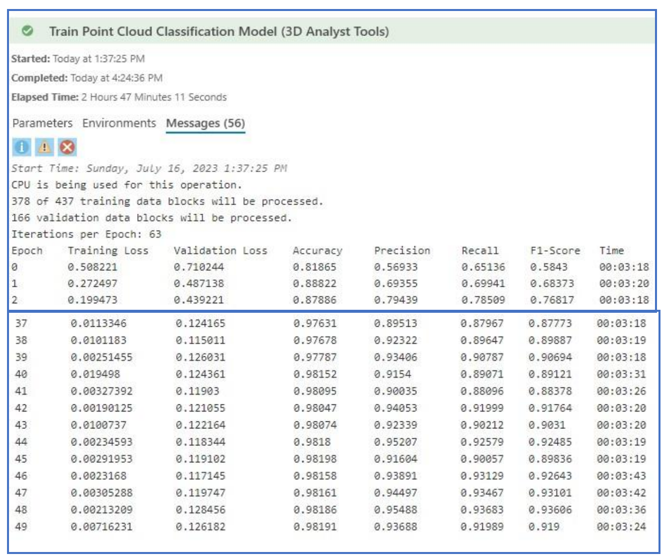


Figure 4. Fully rendered detail image.



Train Point Cloud Classification Model (3D Analyst Tools)

Started: Today at 1:37:25 PM
Completed: Today at 4:24:36 PM
Elapsed Time: 2 Hours 47 Minutes 11 Seconds

Parameters Environments Messages (56)

Start Time: Sunday, July 16, 2023 1:37:25 PM
CPU is being used for this operation.
378 of 437 training data blocks will be processed.
166 validation data blocks will be processed.
Iterations per Epoch: 63

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1-Score	Time
0	0.508221	0.710244	0.81865	0.56933	0.65136	0.5843	00:03:18
1	0.272497	0.487138	0.88822	0.69355	0.69941	0.68373	00:03:20
2	0.199473	0.439221	0.87886	0.79439	0.78509	0.76817	00:03:18
37	0.0113346	0.124165	0.97631	0.89513	0.87967	0.87773	00:03:18
38	0.0101183	0.115011	0.97678	0.92322	0.89647	0.89887	00:03:19
39	0.00251455	0.126031	0.97787	0.93406	0.90787	0.90694	00:03:18
40	0.019498	0.124361	0.98152	0.9154	0.89071	0.89121	00:03:31
41	0.00327392	0.11903	0.98095	0.90035	0.88096	0.88378	00:03:26
42	0.00190125	0.121055	0.98047	0.94053	0.91999	0.91764	00:03:20
43	0.0100737	0.122164	0.98074	0.92339	0.90212	0.9031	00:03:20
44	0.00234593	0.118344	0.9818	0.95207	0.92579	0.92485	00:03:19
45	0.00291953	0.119102	0.98198	0.91604	0.90057	0.89836	00:03:19
46	0.0023168	0.117145	0.98158	0.93891	0.93129	0.92643	00:03:43
47	0.00305288	0.119747	0.98161	0.94497	0.93467	0.93101	00:03:42
48	0.00213209	0.128456	0.98186	0.95488	0.93683	0.93606	00:03:36
49	0.00716231	0.126182	0.98191	0.93688	0.91989	0.919	00:03:24

Figure 5. Training loss and validation loss progression.

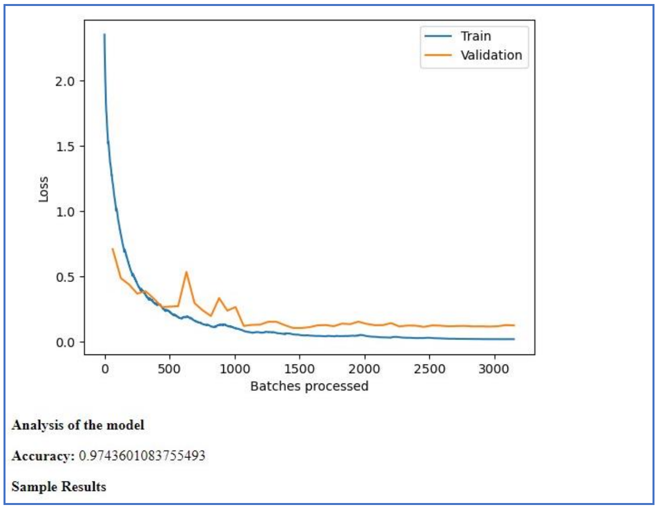


Figure 6. Ground truth / predictions: Loss versus batches processed.

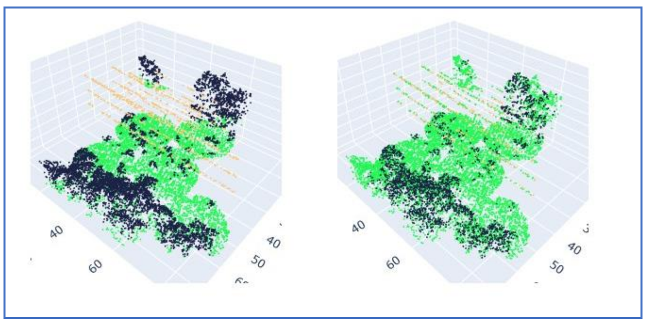


Figure 7. Ground truth / predictions: 3D graphs.

	A	B	C	D	E	F
1	EPOCH	CLASS_CODE	CLASS_DESCRIPTION	PRECISION	RECALL	F1_SCORE
2	31	1	Unassigned	0.972693283	0.994497942	0.983444022
3	38	1	Unassigned	0.974883226	0.994331473	0.984460706
4	30	1	Unassigned	0.952662858	0.993794284	0.972646059
5	37	1	Unassigned	0.974308914	0.992460495	0.983230258
6	32	14	Wire Conductor	0.926027353	0.992211066	0.941156998
7	34	1	Unassigned	0.957427664	0.992102668	0.974271345
8	15	14	Wire Conductor	0.903094753	0.992043357	0.925726761
9	32	1	Unassigned	0.973381023	0.991933699	0.982511344
10	28	14	Wire Conductor	0.903420316	0.991588214	0.925962781
11	18	14	Wire Conductor	0.9188984	0.991575781	0.936937564
12	19	14	Wire Conductor	0.917575678	0.991234439	0.935845536
13	17	14	Wire Conductor	0.932062469	0.990922666	0.945371814

Figure 8. Highest recall value for 14 – Wire Conductor.

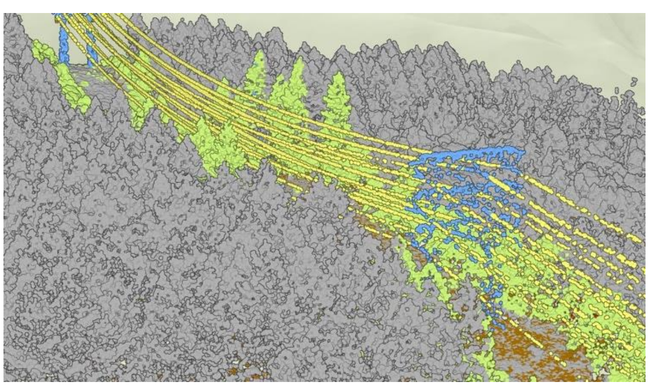


Figure 9. Test run.

The best epoch was chosen based upon the highest recall value for 14 – Wire Conductor. As shown in Fig. 8, that was Epoch 32 with a recall value of 0.992211066 for 14 – Wire Conductor.

A test run used the trained model to classify 3.2 million cloud points previously comprised of ground points (Class 2), low-noise points (Class 7) and unassigned points (Class 1) and classified them into Wire Conductor (Class 14) in yellow, Transmission Tower (Class 15) in blue, High Vegetation (Class 5) in green, and Unassigned (Class 1) in gray (Fig. 9).

IV. CONCLUSION AND FUTURE WORK

The aim of this paper was to demonstrate a proof of concept for a LiDAR point-cloud data-processing tool and explore the potential benefits associated with such a tool. LiDAR is widely used for various applications, including mass asset surveys, vegetation management, and structural-load analysis. The authors explored various ArcGIS geoprocessing tools as part of their study:

- Classify LAS Ground: This tool identifies ground points in LiDAR data.
- Classify LAS Building: This tool is used to classify building points.
- Classify LAS by Height: This tool segments points based on height.
- Classify LAS Noise: This tool identifies noise points.
- Change LAS Classification Codes: This tool allows modification of classification codes.

Next steps and future work include importing LiDAR data, converting LAS to LASD, and offering a step-by-step guide to classifying the converted LAS point-cloud data using the trained model. In summary, this paper provides valuable insights into using ArcGIS tools for LiDAR processing and highlights the potential benefits of accurate geolocation data extraction from LiDAR point clouds within utility service territories.

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