CLOSED: A Dashboard for 3D Point Cloud Segmentation Analysis using Deep Learning

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Keywords: Segmentation, Point Clouds, Analysis, Dashboard, Data Visualization, Deep Learning.

Abstract: With the growing interest in 3D point cloud data, which is a set of data points in space used to describe a 3D object, and the inherent need to analyze it using deep neural networks, the visualization of data processes is critical for extracting meaningful insights. There is a gap in the literature for a full-suite visualization tool to analyse 3D deep learning segmentation models on point cloud data. This paper proposes such a tool to cover this gap, entitled point CLOud SEgmentation Dashboard (***CLOSED***). Specifically, we concentrate our efforts on 3D point cloud part segmentation, where the entire shape and the parts of a 3D object are significant. Our approach manages to (i) exhibit the learning evolution of neural networks, (ii) compare and evaluate different neural networks, (iii) highlight key-points of the segmentation process. We illustrate our proposal by analysing five neural networks utilizing the ShapeNet-part dataset.

1 INTRODUCTION

Nowadays, deep learning is a highly studied field. However, the detailed evaluation of such highly complex intelligent models is still an open issue due to the presence of millions of configurations, parameters, and characteristics to tune (Dargan et al., 2019). Recently, the need for better interpreting the results of these techniques has appeared in the literature (Chatzimparmpas et al., 2020). Going beyond the accuracy-related performance metrics of deep learning models, other crucial factors should be considered in the evaluation process, such as the evolution of learning of the model and/or the required time and/or the resources to finish the learning process (Zoumpekas et al., 2021; Garcia-Garcia et al., 2018). Furthermore, in complex data formats, such as the point clouds, the interpretation of the results ends up being more challenging.

A point cloud is a set of data points in space that represents a 3D shape or object, characterized by x, y, and z coordinates and sometimes by color features and intensity. Neural networks are considered the most suitable models to handle and segment the huge amount of points (i.e millions in most of the cases) that a 3D point cloud dataset contains (Bello et al., 2020). In this segmentation process, it is important not just to analyze the accuracy of the learning, but also to understand the learned parts of an object and later visualize them (Nguyen and Le, 2013). In the field of segmentation analysis, different neural network architectures have been proposed recently to segment inner structures of point cloud, such as (Qi et al., 2017a; Qi et al., 2017b; Yan et al., 2020). However, it is a daunting task to decide which is the most appropriate of them in each context. It depends strongly on a considerable number of characteristics, such as the parameters of the neural network itself, the topology and shape of the object to be segmented, the required learning time, the number of utilized datasets, etc. Moreover, detailed performance evaluation has a significant role in selecting the best neural network and especially presents a high significance in point cloud segmentation analysis, because of the millions of points to segment.

Specifically, it is crucial to identify the characteristics of the hardest and the easiest classes of point clouds to learn or to determine in which iteration you should stop the learning process. It is also important to visually compare and check the values of the various performance metrics with the actual rendering of the resulted point cloud. Thus, evaluating in detail the performance of a set of different deep learning mod-

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Zoumpekas, T., Molina, G., Puig, A. and Salamó, M.
CLOSED: A Dashboard for 3D Point Cloud Segmentation Analysis using Deep Learning.
DOI: 10.5220/0010826000003124
In *Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2022) - Volume 4: VISAPP*, pages 403-410
ISBN: 978-989-758-555-5; ISSN: 2184-4321

els on such highly complex and unstructured data, i.e. point clouds (Bello et al., 2020), with just plain metric values on various occasions and conditions can be an overwhelming task. Thus, there is a need of a dashboard visualization environment to aid users analyse, compare and understand the trends and the insights in complex data relationships (Friendly, 2008).

The advances in computer graphics and the need for complex evaluation analysis of explanatory intelligent machine learning algorithms bring to the foreground the full-suite visualization systems, namely dashboards (Pappas and Whitman, 2011), which may incorporate a vast majority of metrics, graphs, complex animations according to the exact case study.

In this paper, we present an interactive dashboard to facilitate the 3D point cloud segmentation analysis, named point CLOud SEgmentation Dashboard (***CLOSED***) aiming to evaluate and visualize in depth different aspects of the neural networks' learning process. Some specific properties of ***CLOSED*** are: (i) Ability to compare different deep learning models by visualizing a variety of performance metrics, (ii) Evaluation of individual model performance on each learning epoch in order to analyse their improvement in time, (iii) Meaningful insights on the model failures and successes on part segmentation by visualizing sampled shapes of a point cloud dataset. The software of ***CLOSED*** is available at GitHub in the following repository: *https://github.com/thzou/CLOSED_dashboard*.

2 RELATED WORK

There has been a rise in demand for dependable graph representation tools for improving neural networks' trust and explainability driving researchers to investigate interactive visualization tools (Chatzimparmpas et al., 2020). Also, transparency of machine learning through visualizations, monitoring and interpretable results is considered essential for both academic and industrial users (Zhou and Chen, 2018).

Many methods and visualizations have been proposed to aid the segmentation processes in the 2D domain, such as (Faulkner and Bhandarkar, 2003). In the 3D domain, the existence of visualization tools for monitoring and enhancing intelligent procedures are fairly new. ModLayer is an interactive graphical user interface for engaging with 3D data in MATLAB programming environment (Hanhan and Sangid, 2019). Also, (Escalera et al., 2011) presented a complete framework of intelligent techniques to label multiple regions of interest in 3D volumetric representations. Moreover, (Sampathkmar et al., 2017) proposed a 3D visualization framework with multiple applications in natural, biomedical, and aerial photography segmentation. Other studies offer visualization and segmentation of 3D medical images through haptic rendering and stereo graphic operations (Nyström et al., 2009), highlighting the need for efficient interactive tools for segmentation and visualization in 3D medical images. The need for 3D point cloud visualization to facilitate users is highlighted also in some research studies, such as (Richter and Döllner, 2014), where Richter et al. utilize a web-based visualization software to enable the better exploration of 3D point clouds.

However, the majority of the studies focus on correcting and improving concrete segmentation methods rather than providing a comparison tool that allows the end-user to evaluate, compare and decide the best segmentation strategy according to the available objects. Thus, in an attempt to cover the identified gap of visualization tools for 3D point cloud analysis, we propose the ***CLOSED*** tool. Following, we provide the conceptualization of our study and description of our software. Finally, we portray a showcase of ***CLOSED*** involving practical visualization examples.

3 CONCEPTUALIZATION

In this section, we detail the concepts needed to frame our dashboard visualization tool.

3.1 Deep Learning Models: Neural Networks

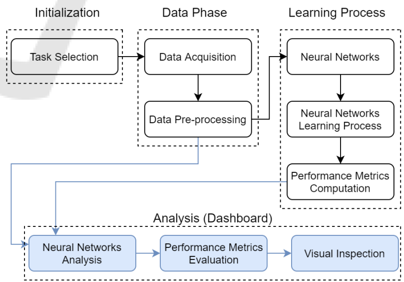


Figure 1: Process overview - Analysis of point cloud data using neural networks.

Neural networks are computational models able to learn multiple degrees of abstraction for data representations using several processing layers (Butkus and Lukoševičius, 2018). The overview of the process of analyzing point cloud data using neural networks is depicted in Figure 1. This procedure involves four stages: Initialization, Data Phase, Learning Process and Analysis. First, the Initialization stage is devoted to the formulation of the problem and the selection of the task to be analysed. The second stage is responsible for the data acquisition and its pre-processing, which involves the separation of the point cloud datasets in different classes depending on the type of the objects that they contain. Hence, each class, i.e. type of object, is represented by a set of point cloud files, or alternatively, instances. Each class may include numerous point cloud objects (instances). In the third stage, there is the selection of the right neural network models for the task to be solved. Also, the training, validation and testing of them and the computation of the performance metrics for evaluation purposes take place in this stage. The results of the Learning Process are used as input in the final stage of the process, the Analysis, where the dashboard visualization tool takes part in. The proposed data visualization dashboard facilitates the interpretation of the whole modeling process by visually analyzing the models, comparing the performance metrics and providing information on the performance of each individual model.

3.2 Evaluating Neural Networks: Performance Metrics

In the segmentation performance analysis, it is important to include not only learning-related metrics, such as the accuracy metrics, but also system-related metrics, such as total runtime and memory allocation (Garcia-Garcia et al., 2018; Zoumpekas et al., 2021). It is also crucial to select the right model for an individual's needs according to the trade-off between the learning-related and system-related metrics.

The commonly used learning-related (or accuracy) metric in point cloud segmentation is based on Intersection over Union IoU. The majority of the studies in segmentation analysis utilize this metric and variants of it, such as (Qi et al., 2017a; Qi et al., 2017b; Thomas et al., 2019; Liu et al., 2020; Liu et al., 2019). We use two of the most used variants of the IoU, the mean Intersection over Union ($mIoU$) obtained by averaging across all Classes of the labelled point clouds ($CmIoU$) and all Instances of all classes ($ImIoU$), both detailed at (Liu et al., 2019).

Generalized metrics taking into account both system-related and learning-related metrics appear in (Zoumpekas et al., 2021), entitled the F_{CmIoU}, F_{ImIoU} and $F_{general}$ segmentation performance metrics. The parameters (α and β) of the aforementioned metrics provide a trade-off between accuracy and efficiency. It should be noted that the process of analysing the values of α and β leads to the selection of the best neural network model.

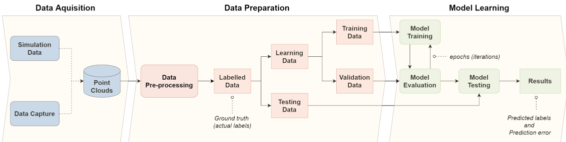


Figure 2: Data processing workflow.

3.3 Description of Data Processing

The management and the processing of the point cloud data along the process are illustrated in Figure 2. Initially, in Data Acquisition phase, point cloud data is collected either from capturing devices (i.e. real data), or simulations (i.e. synthetic data). The pre-processing of the data takes place after the data collection step, in Data Preparation phase, and it mainly involves the cleaning of the data from noise and missing values among other tasks. In the case of segmentation process, the outcome of this step is labelled point clouds with annotated inner regions (parts) of the object. Mainly, each point cloud belongs to a labelled class and has annotated (segmented) parts. Synthetic datasets are often already labelled and annotated. However, real data need to be labelled and annotated in the Data Pre-processing phase.

Then, the Labelled Data is split in Learning Data and Testing Data. Learning data are used to train (Training Data) and validate (Validation Data) the selected neural network model. The process involves several iterations (epochs) between Model Training and Model Evaluation, wherein each iteration the neural network is trained using the Training Data and then validated using the Validation Data in order to update its learning weights, as depicted in the Model Learning stage in Figure 2. The resulted trained neural network model is tested using the Testing Data, in the Model Testing step. Finally, we obtain the results of the Model Learning process. It is worth mentioning that the initial labels of the point clouds can be referred as "*Ground truth*", the predicted ones as "*Predicted*" and the error between them as "*Prediction error*". Please note that, the output of the Model Testing stage includes the results of training, validation and testing phases. These results are comprised of the IoU metrics, GPU_{mem} and t_{total}.

4 *CLOSED* DASHBOARD DESIGN

In this section we explain every analysis capability of ***CLOSED***. The design of the dashboard visualization tool is presented in Figure 3. The initial steps to deploy the dashboard application are the availability of point cloud data and the training of the neural networks in order to assess the performance of them utilizing specific metrics. Afterwards, the dashboard tool uses as input the obtained results of the aforementioned procedure and portrays meaningful insights divided in four distinct tabs.

Briefly, the first tab, entitled *General metrics*, utilizes generalized performance metrics, defined in Section 3.2. The second one, entitled *Per class analysis*, focuses on the performance evaluation of the neural networks regarding each individual class and specifically on how accurately each neural network has learned the distinct classes. The third one, entitled *Model analysis*, emphasizes on comparisons between the neural networks. Finally, the last one presents visual comparisons and quality inspection of the obtained results, which is entitled *Visual inspection*. The ***CLOSED*** visualization dashboard is depicted in Figure 3, where all its tabs are clearly enumerated. Following, we explain in detail the design of each tab.

4.1 Generalized Performance Analysis

The first tab of ***CLOSED***, namely *General metrics*, facilitates the comparisons across different deep learning models based on the generalized metric, $F_{general}$. It provides the ability to interactively weight the segmentation performance between accuracy and time and memory efficiency of the models. We depict the F_{CmIoU}, F_{ImIoU} and the arithmetic mean of those $F_{general}$ in a bar chart format clearly indicating the impact of accuracy and efficiency related metrics in the segmentation performance of each model. It is worth mentioning that the parameters α and β of the equations F_{CmIoU} and F_{CmIoU} respectively, can be adjusted interactively. Additionally, a table shows the results in plain numbers for detail comparisons between the models. Figure 4 depicts a visualization example of this tab. Please note, that a user can interactively add its own neural network learning results in a dedicated panel, entitled "Add Model" in order to be analysed and compared in this tab of ***CLOSED***.

4.2 Per Class Analysis

The aim of the second tab of ***CLOSED***, namely *Per class analysis*, is to compare the segmentation learning-related metrics of *CmIoU* and *ImIoU* of all the trained and tested deep learning models in a chart. We present and compare the *CmIoU* and *ImIoU* values across all learning epochs. Also, we show the obtained *mIoU* per class, which facilitates the detail comparison of deep learning models among different object classes. A user is able to select and display different neural networks, splits of the data, i.e. training, validation and test sets, and classes. Line chart formats are used to show the evolution of the metrics across the epochs and classes. It is worth mentioning that users also can zoom in and out in all the charts as well as hover over the points to see detailed information. Figures 5 and 6 present example charts of the second tab of ***CLOSED***.

4.3 Model Specific Analysis

The aim of the third tab of ***CLOSED***, namely *Model analysis*, is to analyse the individual performance of the neural networks among all the learning epochs. The format of this tab is similar to the second one, i.e. the per class comparison, however this tab focuses on the learning results of each model. Specifically, line charts display the evolution of the *CmIoU* and *ImIoU* metrics among training, validation and test sets and compare them to monitor learning related issues, such as overfitting. Also, a chart depicts how a model performed in each class of the input dataset. The user can select a neural network model and evaluate its accuracy detailed per class of objects along the epochs. Moreover, Figure 7 shows an example of the individual model performance evaluation of this tab.

4.4 Visual Inspection and Comparisons of Sampled Point Clouds

The fourth tab of ***CLOSED***, namely *Visual inspection*, facilitates the analysis of the individual segmentation performance of each model in multiple sampled shapes of point clouds during all the learning epochs. Line charts display the chosen point cloud evaluation metrics detailing the inner segmented parts, i.e. features, such as recall and precision, that are used to evaluate per point accuracy in segmentation in all learning epochs. However, just displaying the graphs of segmentation accuracy is not enough to assess learning failures. Thus, we also include three-dimensional (3D) point cloud renderings to display the sampled point cloud objects, where someone can observe clearly the ground truth, the prediction, and the error in each point cloud. Figures 9 and 8 illustrate examples of visual inspection and comparisons of a specific sampled point cloud.

5 SHOWCASE OF *CLOSED*

This section describes a simulated analysis using the visualizations of ***CLOSED***.

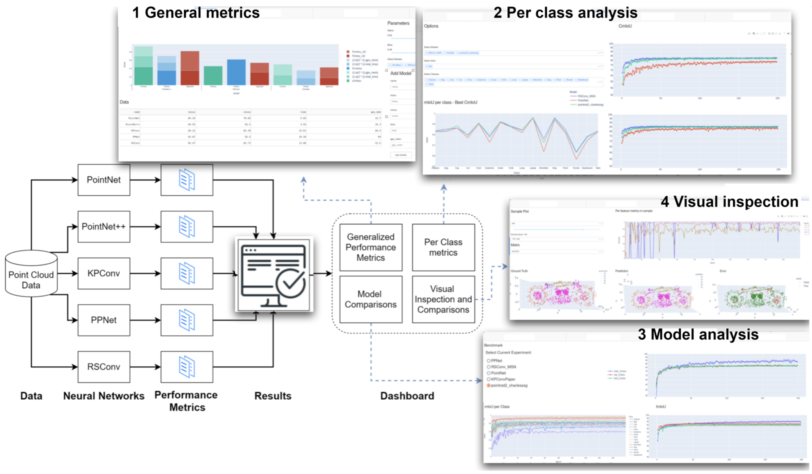


Figure 3: Design of the visualization tool. The numbered pictures denote the 4 distinct tabs of the dashboard.

5.1 Data and Models

The data used in this study is the popular and widely-used ShapeNet data for part segmentation (Chang et al., 2015; Yi et al., 2016). The dataset contains 16881 3D objects of point clouds that are organized in 16 different shape categories (or classes). Each shape category is annotated with two to six parts, having 50 annotated parts in total. The labelled classes of objects are the following: *airplane, bag, cap, car, chair, earphone, guitar, knife, lamp, laptop, motorbike, mug, pistol, rocket, skateboard and table*, in alphabetical order. More information of the ShapeNet data may be found in its official and published papers and repositories (Chang et al., 2015; Yi et al., 2016).

For the simulation of the segmentation process and the task of learning intelligent models from point cloud data, we selected five of the most accurate neural networks[1] for 3D part segmentation analysis. Thus, the utilized deep learning models, i.e. neural networks, are the following: (i) **PointNet** (Qi et al., 2017a), (ii) **PointNet++** (Qi et al., 2017b), (iii) Kernel Point Convolution, abbreviated as **KPConv** (Thomas et al., 2019), (iv) Position Pooling, denoted as **PPNet** (Liu et al., 2020), and (v) Relation Shape Convolution, denoted as **RSConv** (Liu et al., 2019).

5.2 Possible Analysis Aspects

In this section, we show the potential of ***CLOSED*** by answering four possible aspects of the many that could be analysed.

[1]https://paperswithcode.com/sota/3d-part-segmentation-on-shapenet-part

Aspect 1. *According to specific hardware resources and time constraints which neural network model is more appropriate to use?*

Figure 4 presents the generalized performance evaluation (obtained from tab 1 of ***CLOSED***) of the five selected neural networks with parameters $\alpha = 0.5$ and $\beta = 0.5$, concerning balance between segmentation accuracy and efficiency of the deep learning models. Please note that the parameters α and β can be adjusted interactively in range [0,1] according to the needs of the user. For each model, we can observe the $F_{general}$, F_{CmIoU} and F_{ImIoU} and visually compare the proportions of each part of their equations. For instance, comparing the F_{CmIoU} of PointNet++ neural network with the F_{CmIoU} of KPConv, we can say that PointNet++ comes first with $F_{CmIoU} = 0.95$ approximately compared to $F_{CmIoU} = 0.65$ and this is mainly because the KPConv achieves lower values in the efficiency related portions of the metric, i.e. the one related to total run time ($\frac{(1-\beta)}{2} * (1 - t_{total})$) and the one to average GPU memory allocation ($\frac{(1-\beta)}{2} * (1 - GPU_{mem})$). This helps the user to better understand and interpret the proportions of each evaluation metric and how all of them contribute to the general performance. Additionally, this visualization triggers an important practice of creating novel and specialized deep learning architectures, close to the needs of each individual.

Aspect 2. *In which learning epoch we could stop the training process?*

By analyzing Figures 5 (related to tab 2, namely *"Per class analysis"*) and 7 (obtained from tab 3, namely *"Model analysis"*), a user can extract meaningful information on the detection of the exact epoch to stop the learning process of a neural network. It is

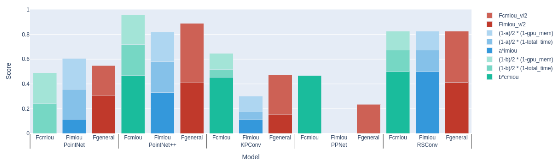


Figure 4: $F_{general}$ metric with $\alpha = 0.5, \beta = 0.5$ on PointNET, PointNET++, KPConv, PPNET and RSConv.

worth noticing that a stop epoch could be the point, where the neural network achieved a significantly high accuracy value in the test data and then its accuracy remains in more or less stable values. For instance, in Figure 5 (b) KPConv achieves an *ImIoU* value of almost 84% at the 25th epoch and then it remains almost constant at this value until the end.

Indeed, *CmIoU* reflexes how well a model performed across all classes, as explained in Section 3.1. Figure 5 (a) displays the evolution of the aforementioned metric in 200 learning epochs of the five selected neural networks in the test data. Also, it can be easily displayed the same but in the training set by using the filtering interactive buttons. Figure 5 (b) portrays the per instance, i.e. per 3D object, *mIoU*, or alternatively the *ImIoU* performance metric. Similarly as in the *CmIoU* occasion, we display the evolution of the *ImIoU* metric in 200 learning epochs in the test data.

Model specific analysis focuses on the per class *mIoU* metric of each model. For instance, Figure 7 presents the *mIoU* segmentation accuracy of PointNet++ model that is obtained across all 200 learning epochs in each class. It can be observed that *laptop* class has almost identical *mIoU* in all the epochs while others, such as *motorbike* start from low values, i.e. harder to learn, and they steadily increase until the last epochs. Thus, depending on the 3D object that we want to focus on, we could stop the learning process earlier or later depending on the target class of segmentation.

Aspect 3. *Which are the most difficult (and easiest) point cloud object classes to learn? Do all the learning models have the same learning behaviour in all classes?*

Each one of the selected deep learning models has its particularities and its special design characteristics. Therefore it is somehow expected that each of them will perform better than the others in specific classes. This is shown in Figure 6 (included in tab 2, namely *"Per class analysis"*), where we can see that, for instance, RSConv performed better than the PointNet and PointNet++ by far in "Motorbike" or "Rocket" class. However, it is worth mentioning that the performance tendency of all models is the same. This fact indicates the presence of "ill" data classes of point cloud objects, which are difficult to segment either because of the lack of enough data or, in general, present more difficulties in feature learning.

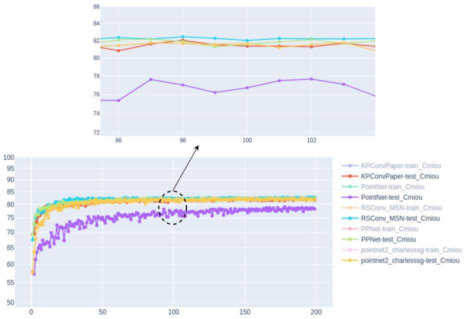
Additionally, Figure 9 (included in tab 4, namely *"Visual inspection"*) shows the per feature metrics of each class, in this occasion, the precision metric. In this way, we provide insights on the correct prediction of each point belonging to a specific feature label. Thus, the information on the performance of both class labels and inner class features aids the identification of the difficult and easy point cloud classes of objects to learn.

Aspect 4. *To what extent the segmentation accuracy metric values are related to the visual representation of the results?*

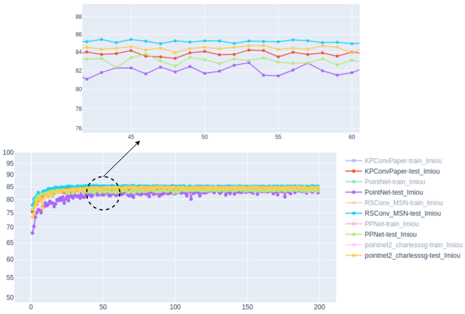
By observing the accuracy metrics in Figures 5, 6 and 7 of the neural network models and object classes, we can visually compare, check and interpret their actual performance. In order to further facilitate the fine-tuning of deep learning segmentation models and to find specific issues on the modelling process, the visualization of sampled point clouds is essential to visually evaluate the results.

In this purpose, for example, we show in Figure 8 (included in tab 4, namely *"Visual inspection"*) the visualization of a chosen sampled point cloud with class label "motorbike". Specifically, we show the initial (actual) sampled point cloud, namely *Ground truth*, the predicted point cloud, *Predicted*, and the error between the actual and the predicted one, *Prediction error* of two selected models, the PointNet and RSConv. For clarification, the demonstrated selection of models has been done according to Figure 6, where PointNet has the worst *mIoU* of about 0.64 in "motorbike" class and RSConv the best one, with approximately $mIoU = 0.77$.

In a randomly selected sampled point cloud instance of the class "motorbike" both models seem to have properly segmented all the annotated parts of the point cloud, as indicated by Figure 8 (e) and (f). However, by focusing on specific points we can identify specific faults of each model and detect in which exact points each model fail. Thus, except for the fine-tuning of specific neural networks, Figure 8 could also provide information for the visual comparison of the actual performance of two or more neural networks. Besides, by zooming into specific error areas in Figure 8 (e) and (f) facilitates the understanding of the pros and cons of different neural network architectures. It is worth noticing that we can choose the exact epoch, out of the 200 epochs of the whole learning process, and display Figure 8.



(a) *CmIoU* metric.



(b) *ImIoU* metric.

Figure 5: Performance evaluation of different neural networks on the test set. The highlighted areas in the graphs show the zooming feature of ***CLOSED***, facilitating the comparisons among the neural networks.

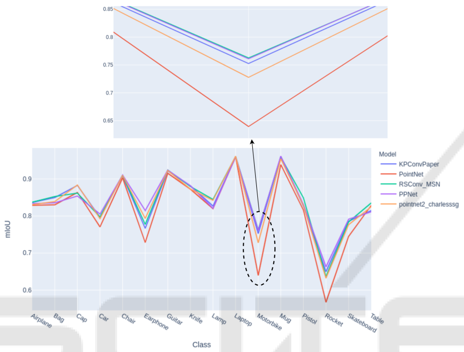


Figure 6: Per class *mIoU* comparison between deep learning models on ShapeNet dataset. In the zoomed and highlighted area, we show the *mIoU* performance of the neural networks in class "motorbike".

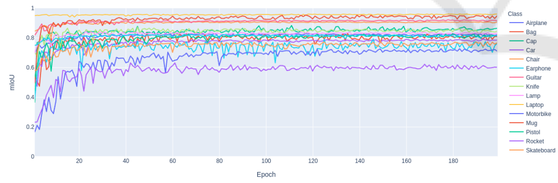
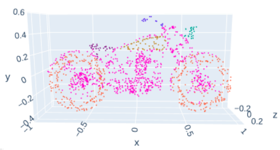


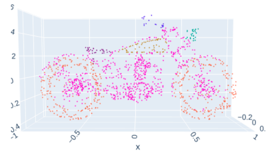
Figure 7: Evolution of *mIoU* metric through training epochs of PointNET++ on ShapeNet dataset.

6 CONCLUSION

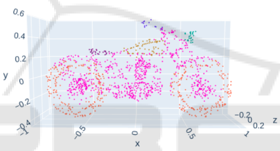
Visualization tools aid to a great extent the analysis of deep learning models and intelligent solutions by offering explainability and interpretability. Also, point cloud segmentation analysis presents a great challenge in the computer science and engineering field. In this paper, we fill the identified research gap in the visualization of 3D point cloud segmentation analysis and facilitate the interpretation of the results of neural networks by proposing the ***CLOSED*** visualization tool. We provide multiple visualizations to answer a



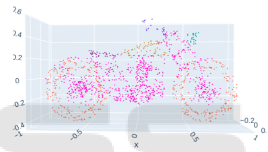
(a) Ground truth - PointNet.



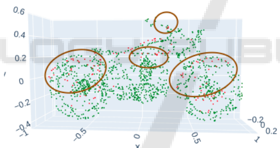
(b) Ground truth - RSConv.



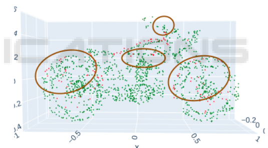
(c) Predicted - PointNet.



(d) Predicted - RSConv.



(e) Prediction error - PointNet.



(f) Prediction error - RSConv.

Figure 8: Sampled point cloud object - Comparisons between models. The different colours in (a), (b), (c), (d) denote the distinct parts of the point cloud. The colours green and red in (e) and (f) denote the correctly and incorrectly predicted points respectively. Also, in (e) and (f), the brown circles highlight example areas that appear to have differences between the two neural networks.

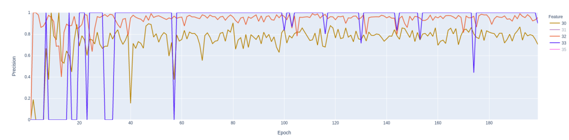


Figure 9: Per feature performance metrics. In this example, we show the *Precision* metric across the 200 epochs of a randomly selected point cloud belonging to class "motorbike", which is achieved by utilizing PointNet++ neural network.

great variety of analysis aspects that may arise during the comparison and selection of neural networks models on 3D part segmentation on point cloud objects. As future work, we plan to enhance the point cloud renderings.

ACKNOWLEDGEMENTS

Marie Skłodowska-Curie Actions

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 860843.

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