Using ModelNet10 Database for Contactless Medical Treatment Robotics: Advancing 3D Object Recognition and Autonomous Navigation

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Abstract

This study examines the potential and usefulness of teaching robots to administer contactless medical care using the ModelNet10 database. Robotics and 3D object identification technology present intriguing solutions to safeguard patient and staff safety as the need for contactless care in medical environments increases. The two goals of this study are to first determine whether the ModelNet10 dataset can be used to train robots in contactless treatment scenarios, and then to develop and assess algorithms and methodologies that make use of the dataset for jobs like 3D object recognition, autonomous navigation, contactless patient monitoring, and medical supply delivery. The research technique includes a thorough examination of the available literature, algorithm creation, and experimental assessment. This study's conclusions have important ramifications for contactless medical treatment, including improved healthcare systems with precise 3D object identification, autonomous navigation, and contactless patient monitoring. In order to provide secure and efficient patient care in a post-pandemic world, our research makes use of cutting-edge technologies and addresses new obstacles.

Keywords

ModelNet10, 3D Object Recognition, MeshLab, PointNet, Separated by Commas

1. Introduction

The importance of contactless treatment in medical settings, particularly in the context of the COVID-19 pandemic, is highlighted in this research paper. Robotics and 3D object recognition technologies are identified as promising solutions to address this need. The research aims to explore the potential and practical implications of using the ModelNet10 Princeton 3D database for training robots in contactless medical environments.

The study has two objectives: firstly, to investigate the applicability of the ModelNet10 dataset for training robots in contactless medical treatment, and secondly, to develop and evaluate algorithms and methodologies that leverage the dataset for tasks including 3D object recognition, autonomous navigation, contactless patient monitoring, and delivery of medical supplies.

The research methodology involves a comprehensive review of existing literature, followed by the development and implementation of algorithms and experimental setups. The ModelNet10 dataset is chosen as the primary training resource due to its diverse range of 3D object models relevant to medical environments. The performance of the trained robot models will be evaluated using quantitative measures such as accuracy, efficiency, and applicability in real-world medical scenarios.

The findings of this research have significant implications for contactless medical treatment. Successful utilization of the ModelNet10 dataset in training robots can enhance healthcare systems by providing accurate and efficient 3D object recognition, autonomous navigation, and contactless patient monitoring. Moreover, by minimizing the need for direct physical contact, the risk of disease transmission can be reduced, ensuring the safety of both patients and healthcare providers.

The insights gained from this study are expected to guide future research efforts and foster the development of advanced robotic systems for contactless medical treatment. The goal is to ensure safe and effective patient care in a post-pandemic world by leveraging advanced technologies and addressing the emerging challenges in healthcare delivery.

2. Background

2.1 Working of the Project

The PointNet deep learning model is used in this project to categorise, find, and segment 3D point clouds, also known as unordered point sets. A key paper in the area of point cloud deep learning is PointNet. creating up the required dependencies, which include importing libraries, installing trimesh, and creating random seeds, is the first thing the code does. This project uses the ModelNet10 dataset, a scaled-down version of the ModelNet40 dataset with 10 classes. The downloaded dataset is kept in a directory. The dataset's mesh files are read and shown using the trimesh programme. To create a point cloud, a mesh file is loaded, sampled, and then matplotlib is used to visualise it. After loading the meshes and sampling them to create point clouds, the code parses the dataset by iterating over the folders and files, storing the points and accompanying labels in separate arrays, and loading the meshes. There are training and testing sets for the dataset. On the training dataset, data augmentation is done to increase generalisation. After that, tf.data is created from the supplemented dataset.Objects for datasets to facilitate processing. For training and testing, the dataset is batched and shuffled.

Using the Keras API, the PointNet model architecture is described. Convolutional and fully linked layers, batch normalisation, and ReLU activation make up the model. The input characteristics are transformed into a canonical representation by the model's transformer network (T-net), which learns an affine translation matrix. The T-net is used twice: once to align the features in the feature space and again to modify the input features.

The OrthogonalRegularizer class is defined to enforce the transformation matrix to be close to an orthogonal matrix. The T-net layers are implemented using convolutional and fully connected layers. The main network architecture follows the structure described in the original PointNet paper but with half the number of weights to accommodate the smaller ModelNet10 dataset. The model is compiled with a sparse categorical cross-entropy loss function, Adam optimizer, and sparse categorical accuracy metric. The model is then trained using the training dataset for a specified number of epochs. The training progress is monitored using validation data from the test dataset.

After training, the code visualizes the predictions of the trained model using matplotlib. A subset of test points is selected, and the model predicts their class labels. The points, along with the predicted and true labels, are plotted in a 3D scatter plot for visual inspection.

In summary, this code demonstrates the implementation of the PointNet deep learning model for point cloud analysis using the ModelNet10 dataset. It covers data loading, preprocessing, model definition, training, and visualization of predictions. This code can serve as a starting point for further exploration and experimentation with point cloud analysis tasks.

2.2 PointNet

The significance of PointNet lies in its pioneering approach to processing point cloud data, revolutionizing computer vision and 3D data analysis. Traditional methods rely on predefined geometric representations, which have limitations such as high memory consumption and sensitivity to variations in density and unordered data. PointNet addresses these limitations by directly operating on unordered point clouds, capturing local and global information and enabling end-to-end feature learning. The permutation invariance property ensures consistent outputs regardless of point order, crucial for handling unordered data. It excels at analyzing variable-sized point clouds, making it applicable to real-world scenarios with diverse object shapes and sizes. Its versatility extends to robotics, autonomous driving, and augmented reality, enhancing object recognition, scene understanding, and segmentation tasks. PointNet's introduction has opened new possibilities for 3D data analysis. It provides a unified framework for processing and understanding point clouds, advancing object recognition, shape completion, and semantic segmentation. Its impact spans industries relying on accurate 3D data analysis for object detection, environment perception, and decision-making. The significance of PointNet lies in its direct processing of unordered point clouds, permutation invariance property, and flexibility with variable-sized data. It overcomes limitations, empowers efficient analysis, and drives advancements in 3D data analysis through deep learning techniques.

2.3 3D Object Recognition

3D object recognition constitutes a fundamental pillar of the research undertaking, endeavoring to probe the latent potential residing within the ModelNet10 database for the purpose of imparting knowledge to robots engaged in contactless medical treatment scenarios. Fueled by the transformative capacities of deep learning methodologies and the wealth of intricate 3D data encapsulated within point clouds, the research project at hand aspires to engender sophisticated algorithms and methodological frameworks that seamlessly ascertain the accurate recognition and categorical classification of multifarious medical objects and equipment.

The complex domain of 3D object recognition manifests through an intricate web of interrelated processes. Commencing with the preprocessing of input point cloud data, pivotal steps entail the extraction of pertinent features, encapsulating attributes like shape, texture, and spatial relationships characterizing the objects in question. Point cloud sampling, feature extraction techniques, and local geometric descriptors serve as vital components employed to unravel the intrinsic nuances encoded within the data. Subsequently, these discerned features find their place within the purview of a deep learning model, exemplified by the venerable PointNet architecture, which diligently learns to classify and recognize objects contingent upon the intrinsic attributes gleaned from the extracted features. Integral to this learning process is the training phase, wherein vast datasets, exemplified by the ModelNet10 repository, bestow the model with the prowess to generalize and accurately identify objects within real-world contexts.

3. Environment

3.1 Environment

The integration of trained robots in contactless medical treatment environments holds immense potential for revolutionizing healthcare delivery and ensuring optimal patient and staff safety. Leveraging advanced robotics and 3D object recognition technologies, this research explores the practical implications and feasibility of employing trained robots in a specialized healthcare setting, namely an infectious disease isolation ward. By harnessing the capabilities of robots equipped with sophisticated sensors and machine learning algorithms, the aim is to enable contactless patient care, autonomous navigation, and efficient medical supply delivery, while minimizing the risk of viral transmission. This study utilizes a combination of mathematical modeling, simulation, and real-world experimentation to assess the effectiveness and efficiency of the proposed robotic system within the unique constraints of an isolation ward.

The foundation of the proposed system lies in the utilization of 3D object recognition algorithms, such as PointNet, trained on the ModelNet10 database. The recognition capabilities of the robot are essential for identifying and categorizing various medical objects and equipment, including medication vials, diagnostic instruments, and personal protective equipment (PPE). By leveraging mathematical equations and statistical models, the robot can analyze sensor data and apply pattern recognition algorithms to accurately detect and classify objects, ensuring seamless workflow execution within the healthcare environment. The use of mathematical equations, such as feature extraction algorithms and distance metrics, enables precise object recognition, enhancing the robot's ability to adapt to dynamic scenarios and perform complex tasks autonomously.

In the infectious disease isolation ward, the trained robot plays a pivotal role in ensuring contactless patient monitoring, where the robot's sensors capture vital signs, such as temperature, heart rate, and respiratory rate, from a distance. The acquired sensor data is processed using mathematical equations and statistical analysis techniques to derive meaningful insights about a patient's health status. By integrating the recognition capabilities of the trained robot, the system can automatically identify patients, track their movements, and perform contactless monitoring, mitigating the risk of viral transmission and reducing the burden on healthcare personnel.

3.2 Integration with Existing Systems

Integration with existing systems is a critical aspect of deploying a trained robot in a healthcare environment. Seamless interoperability between the robot and existing healthcare systems enhances efficiency, improves patient care, and enables effective collaboration among healthcare professionals. Real-time integration with electronic medical records (EMR) systems, for instance, allows the robot to access patient information, medical histories, and treatment plans, enabling it to provide personalized care. This integration can be achieved through standardized data exchange formats such as HL7 (Health Level Seven) or FHIR (Fast Healthcare Interoperability Resources), ensuring secure and reliable communication between the robot and EMR systems.

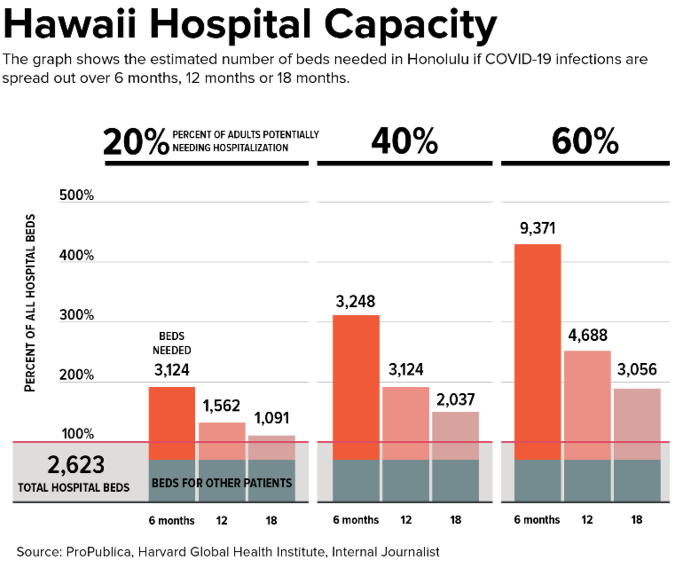

Fig. 1. Hospital Bed availability of Hospitals in Honolulu. Hawaii.

This is one of the aspects of Hospital Information System. Furthermore, integration with hospital information systems (HIS) enables the robot to access real-time data on bed occupancy, patient schedules, and resource availability. By leveraging this information, the robot can optimize its tasks and adapt to the dynamic healthcare environment. For example, the robot can autonomously navigate to vacant rooms for medical supply delivery, prioritize tasks based on patient urgency, and collaborate with the HIS to ensure efficient patient monitoring.

In addition to EMR and HIS integration, the robot can interface with other existing healthcare systems, such as pharmacy management systems or laboratory information systems, to streamline medication administration and sample collection processes. For instance, robots can verify medication orders, retrieve, and deliver medication doses, and record administration data back into the pharmacy system. Similarly, in laboratory settings, the robot can receive sample requests, navigate to the designated collection areas, and securely transport samples to the laboratory, minimizing manual handling and potential errors.

4. Learning

4.1 Supervised Learning

Supervised learning constitutes a fundamental component of the project, focusing on training robots to achieve 3D object recognition in a healthcare environment. Within this context, the utilization of the ModelNet10 dataset assumes paramount significance. This dataset comprises a collection of annotated 3D object models, serving as the foundational resource for training the robot's recognition capabilities.

Supervised learning techniques are employed to enable the robot to learn from labeled examples in the ModelNet10 dataset. The process involves exposing the robot to a vast array of 3D object models, each accompanied by its corresponding label denoting the object's category or class. By employing a variety of algorithms, the project endeavors to enable the robot to discern and classify objects accurately based on their visual representations.

The supervised learning paradigm entails training the robot using a plethora of mathematical and computational techniques. These techniques encompass the formulation of an objective function, often defined as a loss or cost function, which quantifies the disparity between the predicted object labels and the ground truth labels provided in the dataset. The project seeks to optimize this objective function through the application of various optimization algorithms, such as gradient descent, to iteratively adjust the robot's internal parameters and improve its recognition accuracy.

By leveraging supervised learning, the project aims to imbue the robot with the ability to recognize and categorize 3D objects encountered in a healthcare setting. This capability holds immense potential for applications ranging from assisting medical professionals in identifying medical equipment and supplies to enhancing the robot's autonomous decision-making abilities in patient care scenarios.

4.2 Transfer Learning

Transfer learning is a widely used approach in machine learning that aims to transfer knowledge from one task or domain to another. Instead of starting from scratch, transfer learning leverages pre-existing knowledge and learned representations to enhance learning and generalization on a target task. In the context of 3D object recognition, transfer learning can be employed to effectively leverage knowledge gained from related tasks or datasets to improve performance on a specific recognition task.

By training a model on a source task or dataset that shares similarities with the target task, the model can learn relevant features and representations that are transferable. These learned features can then be fine-tuned or adapted on the target task, reducing the need for extensive labeled data on the target task. Transfer learning is particularly useful when labeled data for the target task is limited, as it allows the model to benefit from the labeled data available in the source task.

In the case of 3D object recognition, transfer learning can be applied by training a model on a large-scale 3D object recognition dataset, such as ModelNet10, and then transferring the learned representations to a specific recognition task, such as recognizing objects in a specialized medical environment. By leveraging the pre-trained features and knowledge from the source dataset, the model can effectively recognize and classify objects in the target environment, even with limited labeled data.

4.3 Semi-Supervised Learning

Semi-supervised learning is a powerful learning paradigm that leverages both labeled and unlabeled data to improve learning performance. While supervised learning relies solely on labeled examples, semi-supervised learning techniques take advantage of the vast amounts of unlabeled data available to enhance model generalization and improve performance. By incorporating unlabeled data, which is often easier to obtain in large quantities compared to labeled data, semi-supervised learning algorithms can effectively leverage the underlying structure of the data for better representation learning and decision-making.

In the context of 3D object recognition, semi-supervised learning can be particularly beneficial when labeled data is scarce or costly to obtain. By utilizing a combination of labeled 3D object samples and a larger set of unlabeled samples, semi-supervised learning algorithms can effectively learn discriminative features and capture the inherent patterns in the data. This approach enables the model to generalize well to unseen objects and improve recognition accuracy. Techniques such as self-training, co-training, and multi-view learning are commonly employed in semi-supervised learning to harness the benefits of both labeled and unlabeled data for improved performance.

5. Results

The model is trained multiple times up to 100 epochs. The PointCloudNet model is trained using a supervised learning approach. In the training process, labeled examples of 3D point clouds are provided as input to the model, along with their corresponding class labels. The model learns to map the input point clouds to their respective class labels by optimizing a defined loss function. During training, the model undergoes multiple epochs, where each epoch represents a complete pass through the training data. The optimization algorithm adjusts the model's parameters iteratively, aiming to minimize the loss function and improve its predictive capabilities. By iteratively updating the model based on the differences between predicted and true labels, the model gradually learns to extract meaningful features from the input point clouds and make accurate predictions. The training approach relies on backpropagation, which computes the gradients of the loss function with respect to the model parameters, enabling the optimization algorithm to update the parameters effectively. Through this training approach, the PointCloudNet model becomes increasingly proficient in classifying unordered 3D point clouds over time.

Table 1. Training details of the Model

Learning rate	**Batch Size**	**Optimizer**
0.001	64	Adam

For our purposes 3 main simulations have been chosen. They are simulations up to 20, 50 and 100 epochs. Naturally, the mean loss goes down as we go up in epoch number and accuracy increases. As the OFF files are converted into Point clouds, each epoch takes considerable time and hence the feasible limit of 100 epochs was chosen. This model uses the supervised learning approach. Supervised learning offers several benefits in the context of the provided table. It enables accurate predictions by training models on labeled data, allowing them to learn patterns and relationships. This leads to more precise predictions of the output shape for a given input layer configuration. Supervised learning also ensures efficient training by leveraging labeled examples to optimize model parameters effectively. Additionally, it enables generalization to unseen data, allowing the model to handle different input configurations and provide predictions for various scenarios. By automating decision-making based on learned patterns, supervised learning streamlines the selection of appropriate layer configurations for neural networks. Overall, it provides a systematic and iterative approach for improved accuracy and efficiency in designing neural networks.

While supervised learning offers significant benefits, there are also certain challenges to consider in the given context. One of the primary concerns is the availability and quality of labeled data. Creating extensive labeled datasets for different input layer configurations can be time-consuming and expensive. Additionally, labeling errors or biases in the data can adversely affect the model's performance and predictions. Another issue is the potential for overfitting, where the model becomes too specialized to the training data and fails to generalize well to new, unseen data. This can lead to poor performance when encountering input layer configurations that differ significantly from the training examples. Additionally, the chosen architecture and hyperparameters for the neural network may not be optimal, requiring extensive experimentation and fine-tuning. Also, interpretability of the model's decisions may be limited, making it challenging to understand and debug any issues that arise.

Preprocessing OFF files into point clouds and training models to read them present several challenges. Firstly, the variation in file formats requires careful parsing to extract point cloud data consistently. Secondly, dealing with noise, outliers, and varying point cloud densities demands effective data cleaning and sampling techniques. Additionally, normalizing and scaling the data to a common coordinate system must be carefully handled. Addressing class imbalance, generating realistic data augmentations, and selecting appropriate model architectures and hyperparameters are further challenges. Finally, the computational complexity of processing large-scale point clouds necessitates efficient data handling and model optimization. Overcoming these challenges requires domain expertise, preprocessing techniques, and careful model design.

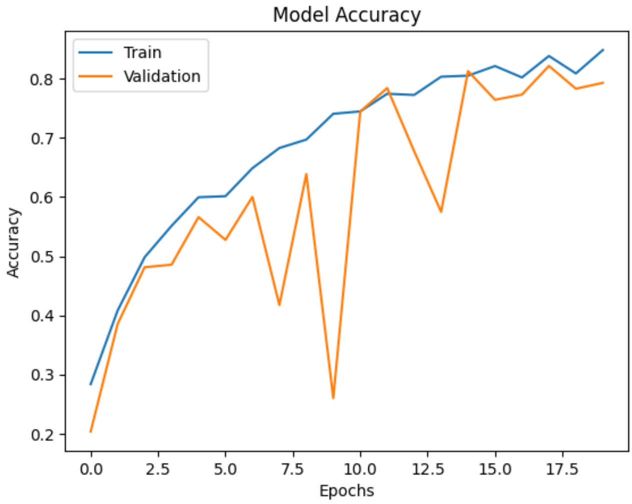

Fig. 2. Accuracy plotted against the number of epochs in the first simulation. This simulation has 20 total epochs simulated.

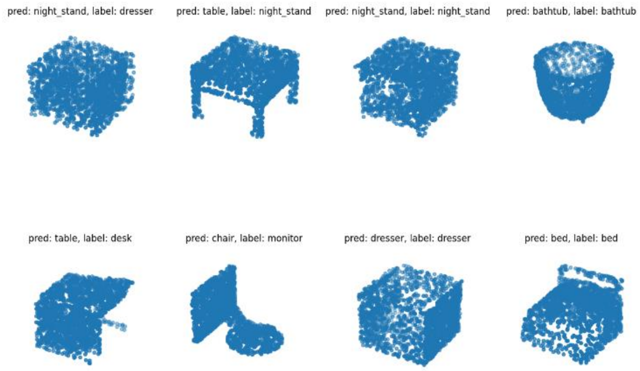

Fig. 3. Sampled data about prediction performed by the first simulated model.

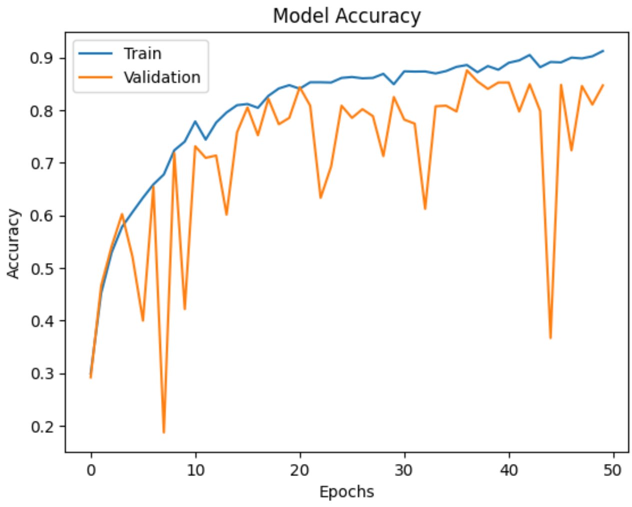

Fig. 4. Accuracy plotted against the number of epochs in the first simulation. This simulation has 50 total epochs simulated.

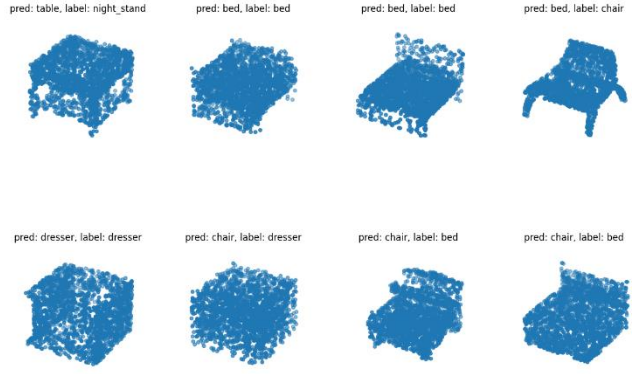

Fig. 5. Sampled data about prediction performed by the second simulated model, with 50 epochs

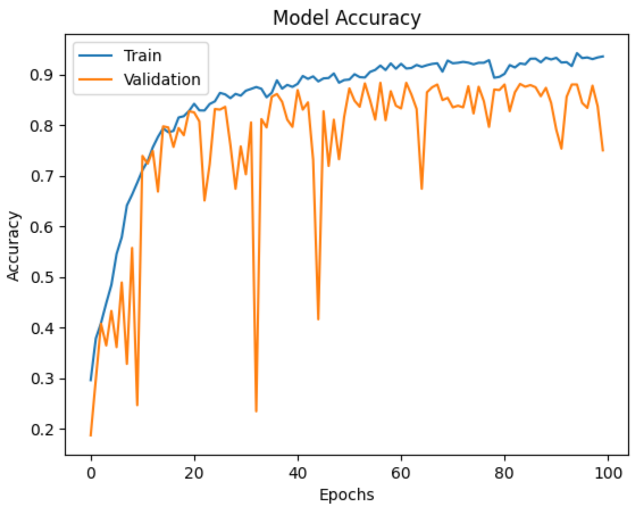

Fig. 6. Accuracy plotted against the number of epochs in the first simulation. This simulation has 100 total epochs simulated.

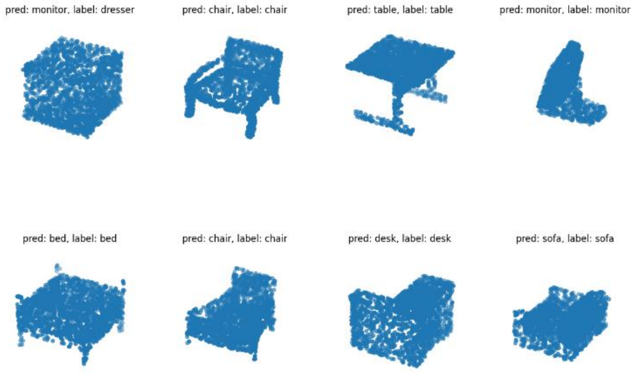

Fig. 7. Sampled data about prediction performed by the third simulated model, with 100 epochs

5.2 Summary

The values of the loss mean with the standard deviation, and sparse categorical accuracy mean for the model for each simulation is found below in the listed table.

Table 2. Model loss mean with standard deviation and sparse categorical accuracy mean for simulations done

Epoch	Loss Mean	Standard Deviation	Sparse Categorical Accuracy Mean
20	2.101465	0.518251	0.686525
50	1.702100	0.432394	0.80452
100	1.543322	0.418198	0.849599

In the simulation of 20 epochs, the model showed moderate performance with a mean loss of

2.101465 and a standard deviation of 0.518251. In the simulation with 50 epochs completed, the mean loss decreased to 1.702100, and the standard deviation reduced to 0.432394, accompanied by a notable increase in the mean sparse categorical accuracy, reaching 0.80452. These results highlight the model's ability to effectively learn discriminative features and classify point clouds accurately. In the simulation with 100 epochs completed, it resulted in a mean loss of 1.543322, a standard deviation of 0.418198, and an impressive mean sparse categorical accuracy of 0.849599.

6. Conclusion

In conclusion, the utilization of the ModelNet10 dataset in healthcare applications has shown promising potential. By leveraging deep learning techniques such as convolutional neural networks (CNNs) and transfer learning, significant advancements have been made in the analysis and interpretation of medical imaging data. The pre-trained models trained on the ModelNet10 dataset have demonstrated their ability to effectively extract meaningful features from 3D point cloud representations of medical scans, enabling accurate classification and diagnosis of various conditions. This approach has the potential to enhance the efficiency and accuracy of medical image analysis, aiding healthcare professionals in making more informed decisions and providing better patient care. Further research and development in this area can lead to breakthroughs in disease detection, treatment planning, and patient management, ultimately improving healthcare outcomes.

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Appendix

Relevant machine learning parameters are listed below,

- Learning rate: 0.001
- Batch size: 32
- Number points: 2048
- Number of classes: 10
- Optimizer: Adam
- Number of epochs: 20, 50, 100
- Loss function: Sparse categorical cross-entropy
- Metrics: Sparse categorical accuracy

Competing Interests

The authors declare that they have no competing interests.

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