Visualizing Veterinary Medical Data Sets with Jetstream

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INTRODUCTION

Background: Veterinary medicine has become increasingly reliant on advanced imaging.

- 3D visualizations of organisms and various regions of interest (ROI) have enhanced diagnosis and treatment procedures for veterinarians.
- Printed models of different animals can be generated from CT datasets.
- Additive manufacturing in particular has been an essential tool in training practices to increase confidence and efficiency of surgical operations.[1]

Problem: Image slices of CT datasets are usually analyzed manually and thus can consume extensive periods of time.

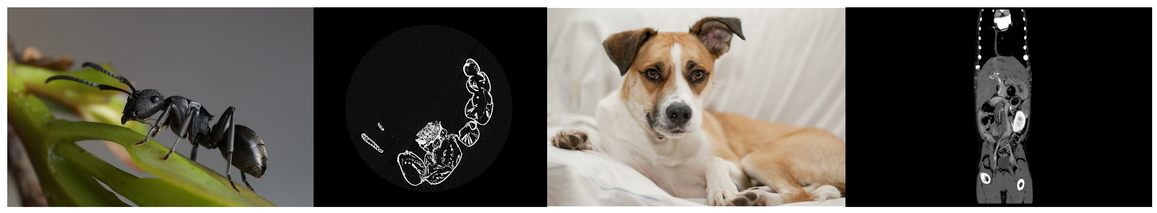
Solution: To facilitate image processing and visualization of CT datasets we created a Jetstream virtual machine (VM) [2]with:

- 3D modeling software for preliminary stages of 3D printed models
- Neural network for classifying CT image slices of different species.

METHODS

Data: DICOM (Digital Imaging and Communication in Medicine) is the standard file format for medical data management (i.e., CT or MRI).

- Ant (*Zasphinctus obamai)*[4] and dog CT data sets were used to perform the additive manufacturing workflow.
  - Ant CT data was retrieved from the Dryad Digital Repository[5]

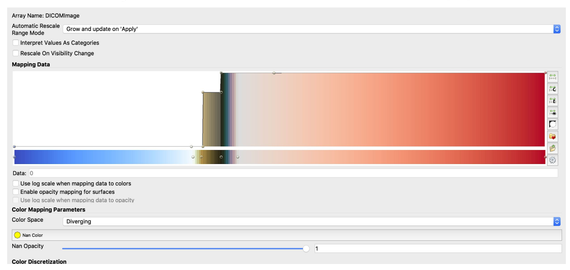


- Additionally, armadillo, horse, snake, and turtle CT datasets were included in the image classification CNN model.

Building 3D Models

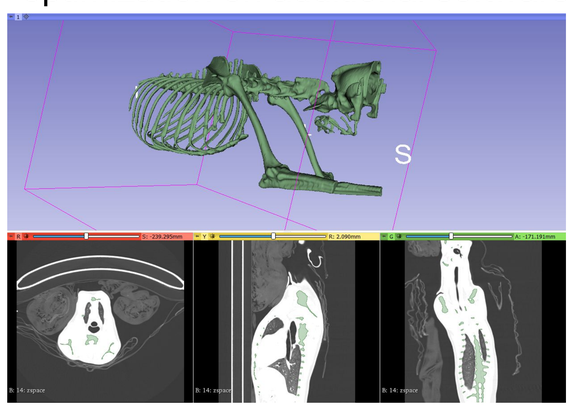
ParaView: 3D volumetric reconstruction of 2D DICOM image files were rendered and customized.

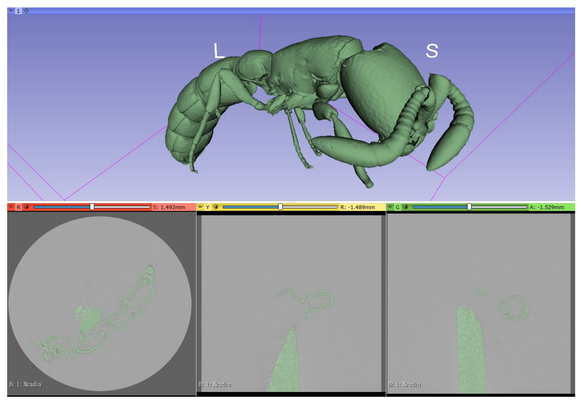
- “Color Map Editor” was used to create unique transfer functions that allowed us to manipulate opacity levels, colors, and brightness of the organism based on varying structural densities of the body or ROI.
- Adjustable visibility of body structures or layers became more apparent.



3D Slicer: Each organism was manually segmented into the desired body layer(s) or segment(s): epidermal, muscle tissues, or skeletal.

- The “Segmentation” and “Segment Editor” modules were used with editing effects such as island erasing, thresholding, and smoothing.
- Stereolithography (STL) files per segment were exported for further optimization on additional software via a local machine.





(Left) Canine interior-skeletal segment (Right) Ant exterior-skin segment (Both) Bottom half, CT slices viewed in the axial, sagittal, and coronal plane, left to right respectively.

METHODS *(continued)*

Convolution Neural Network (CNN): Machine learning algorithm was trained to predict the organism of a given CT image slice in a dataset.

- Input: DICOM files converted to PNG images

CNN IMAGE ALLOTMENTS						
Image Allocation	**Tested CT Datasets**					
	ANTS	DOGS	ARMADILLO	HORSE	SNAKE	TURTLE
Train (80%)	190	214	107	102	221	140
Test (20%)	48	54	27	26	55	35
Total	238	268	134	128	276	175

- Layers[5]: Convolutional with ReLU activation function (3x3 kernel) → Max Pooling (3x3 filter) → Convolutional with ReLU activation function (3x3 kernel) → Dropout→ Max Pooling (3x3 filter) → Flatten→ Dropout→ Dense with Softmax activation function → Normalization→ Dense with Softmax activation function
- Output: Classification certainty (%) of each organism per test image

RESULTS

- Batch size was 100 images in each epoch for all data collection
- Training accuracy tended to increase as number of epochs increased

TRAINING ACCURACY				
Number of Epochs	25	50	75	100
Accuracy (%)	93.240	96.575	97.840	98.353

- Values represent certainties with 100 epochs of training

DESCRIPTIVE STATISTIC: MEAN CLASSIFICATION CERTAINTY							
Tested CT Dataset	**Certainty (%)**						
	Correct	*Incorrect*					
		ANT	DOG	ARMADILLO	HORSE	SNAKE	TURTLE
ANT	88.530	---	3.907	1.756	1.404	2.086	2.318
DOG	77.721	4.457	---	6.514	3.645	4.146	3.512
ARMADILLO	14.152	7.689	48.310	---	5.664	0.280	23.905
HORSE	57.543	3.585	1.772	5.068	--	27.764	4.268
SNAKE	77.684	2.002	3.351	6.612	5.312	--	5.033
TURTLE	95.063	0.915	0.989	2.605	0.244	0.183	---

Non-Parametric ANOVA

- Kruskal-Wallis rank sum test on all species models: chi-square = 93.991, df = 5, $p < 0.0001$
  - Tukey HSD post-hoc comparisons: Turtle Ant Dog Snake Horse Armadillo
    (Underlined species **NOT** significantly different)

DISCUSSION

- Workflow for developing 3D printed models was primarily intended to be functional on Jetstream via a GUI virtual desktop of the VM workstation.
  - Only ParaView was found successfully serviceable on the VM, whereas 3D Slicer had graphical loading issues.
  - Latency problems prompted 3D modeling to be largely done locally.
- CNN exemplified applicability of machine learning in veterinary data analysis, which provides a basis for an image segmentation algorithm.[6]
  - A FCN (Fully Convolutional Network), specifically in a U-Net structure, can be derived for automated segmentation.

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ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under Grant No. 1445604. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.Thank you to Evan Suggs for assistance in CNN implementation. Special thanks and great appreciation for everyone at IU UITS RT that provided help and guidance throughout our REU project: (Jetstream Admin. & Mgmt.) Mike Lowe, George Turner, Steve Bird, Sanjana Sudarshan, & Jeremy Fischer; (Machine Learning-Neural Networking) Jefferson Davis & Laura Huber; (UNIX & Command Line) Sheri Sanders & Bhavya Papudeshi; (Visualization) Eric Wernert; (Writing Editor) Harmony Jankowski.