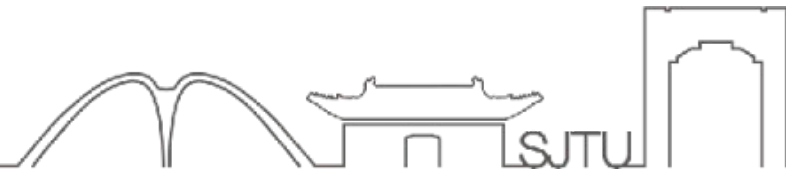




JOINT INSTITUTE
交大密西根学院

Replacing a cloud based computation tool on DrBoxOnline.com with faster running neural network



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Section Instructor

Jigang Wu

Sponsor

Shane Johnson

Group members

- Keye Chen
- Yanzhuo Gao
- Shuo Deng
- Fengyu Zhang
- Yukuan Zhu

Intro: Project Goal Summary

- **Replace FEA with DNN in Dr. Box Calculator Pro:** We aim to replace the current Finite Element Analysis (FEA) method with Deep Neural Networks (DNN) in the Dr. Box Calculator Pro to improve efficiency.
- **Provide instant predictions of buckling strength:** Our goal is to deliver immediate and accurate predictions of buckling strength for various types of corrugated paper boxes.
- **Reduce computational costs and time:** By implementing DNN, we strive to significantly cut down on the time and resources required for analysis.
- **Enhance efficiency and effectiveness in packaging and logistics:** Ultimately, our project aims to boost overall operational efficiency and effectiveness within the packaging and logistics industries.



Intro: Problem Definition

- **Current reliance on FEA is time-consuming and resource-intensive:** The existing method of using Finite Element Analysis (FEA) requires extensive computational resources and a considerable amount of time to perform.
- **Corrugated boxes are prone to buckling, causing damage and losses:** Despite their widespread use due to their lightweight and recyclable nature, corrugated boxes often buckle during storage and shipment, leading to product damage, lost revenue, and increased customer complaints.
- **Need for faster, more reliable prediction methods:** To mitigate these issues, there is a crucial need for a faster and more reliable method for predicting the buckling strength of these boxes.



Intro: Review of Specs and Requirements

- **High predictive accuracy ($\geq 90\%$):** The system must achieve a predictive accuracy of at least 90% to ensure reliable results.
- **Fast analysis (≤ 5 minutes per simulation):** Each simulation should be completed within 5 minutes to facilitate quick decision-making.
- **Ability to handle diverse box types and conditions:** The system should be versatile enough to accommodate various box designs and environmental conditions.
- **System reliability above 99.9%:** The solution should maintain a high level of reliability, with an uptime of more than 99.9%, to ensure consistent performance.

Concept Gen: Accuracy

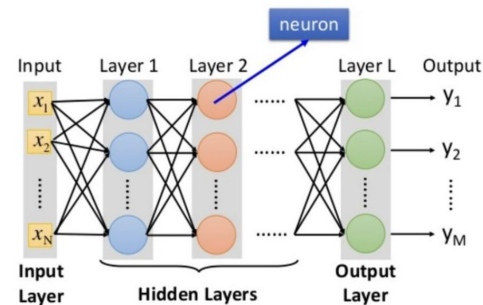
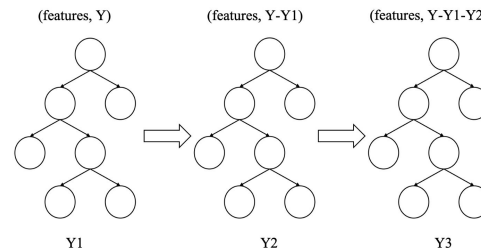
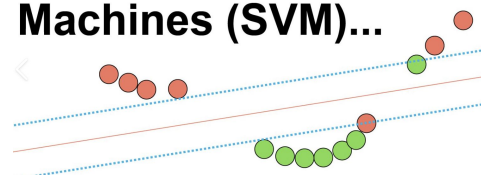
Sub-function requirements:

- Efficient handling of limited numerical data, high prediction accuracy, and ability to manage complex relationships between features and ultra high dimension outputs.

Generated concepts:

- Decision Boosting Trees: Capable of capturing complex, non-linear relationships between features and targets.
- Support Vector Machines (SVM): Effective in high-dimensional spaces and can handle a large number of features.
- Deep Neural Networks (DNN): Capable of learning intricate patterns and relationships in the data through multiple layers of neurons.

Support Vector Machines (SVM)...



Concept Gen: Speed

Sub-function requirements:

- Replace complex and heavy physical calculation formulas with machine learning models.
- Achieve rapid prediction of hundreds of physical deformation features in 3D space using limited input coordinates and features.

Generated Ideas:

- Use simple linear regression models, simple but fast.
- Use deep and wide neural networks, load on GPU to accelerate the training process, hardware and big dataset demanding.
- Parallel calculating.....

Formula No.	Description	Formula	Constraint
1	Tensile Strength	$\sigma_{\max} = \frac{N}{A_{\text{cross-section}}}$	$\leq [\sigma]$
2	Shear Strength	$\tau_{\max} = \frac{Q}{A_{\text{shear}}}$	$\leq [\tau]$
3	Compressive Strength	$\sigma_{\max} = \frac{P}{A_{\text{compression}}}$	$\leq [\sigma_{\text{compression}}]$
4	Torsional Strength	$\tau_{\max} = \left(\frac{M_T P}{I_P} \right)_{\max}$	$\leq [\tau]$
5	Bending Strength	$\sigma_{\max} = \left(\frac{M_N}{W_N} + \frac{M_{Ny}}{W_{Ny}} \right)_{\max}$	$\leq [\sigma]$
6	Combined Tensile (Compressive) and Bending	$\sigma_{\max} = \frac{N}{A} + \frac{M_{\max}}{W_n}$	$\leq [\sigma]$
		$\sigma_{\max}^+ = \frac{N}{A} + \frac{M_{\max}}{I_z} y_{\max}^+$	$\leq [\sigma]^+$
		$\sigma_{\max}^- = \frac{M_{\max}}{I_z} y_{\max}^- - \frac{N}{A}$	$\leq [\sigma]^-$
7	Axial Compressive and Shear Stresses	$\sigma_{\alpha} = \sigma_{\text{horizontal}} \cos^2 \alpha$	
	on Inclined Plane	$\tau_{\alpha} = \frac{\sigma_{\text{horizontal}}}{2} \sin 2\alpha$	
8	Combined Axial and Torsional Stresses	$\sigma_{\text{eq3}} = \sqrt{\sigma^2 + 4\tau^2} = \sqrt{\left(\frac{M_n^2 + M_T^2}{W_n} \right)}$	$\leq [\sigma]$
	(Third Strength Theory)		
8	Combined Axial and Torsional Stresses	$\sigma_{\text{eq4}} = \sqrt{\sigma^2 + 3\tau^2} = \sqrt{\left(\frac{M_n^2 + 0.75M_T^2}{W_n} \right)}$	$\leq [\sigma]$
	(Fourth Strength Theory)		
9	Combined Axial (Compressive) and Torsional	$\sigma_{\text{eq3}} = \frac{1}{W_n} \left(M_n + ND (1 + \alpha^2)^2 \right) + M_T^2$	$\leq [\sigma]$
	Stresses (Third Strength Theory)		
9	Combined Axial (Compressive) and Torsional	$\sigma_{\text{eq4}} = \frac{1}{W_n} \left(M_n + ND (1 + \alpha^2)^2 \right) + 0.75M_T^2$	$\leq [\sigma]$



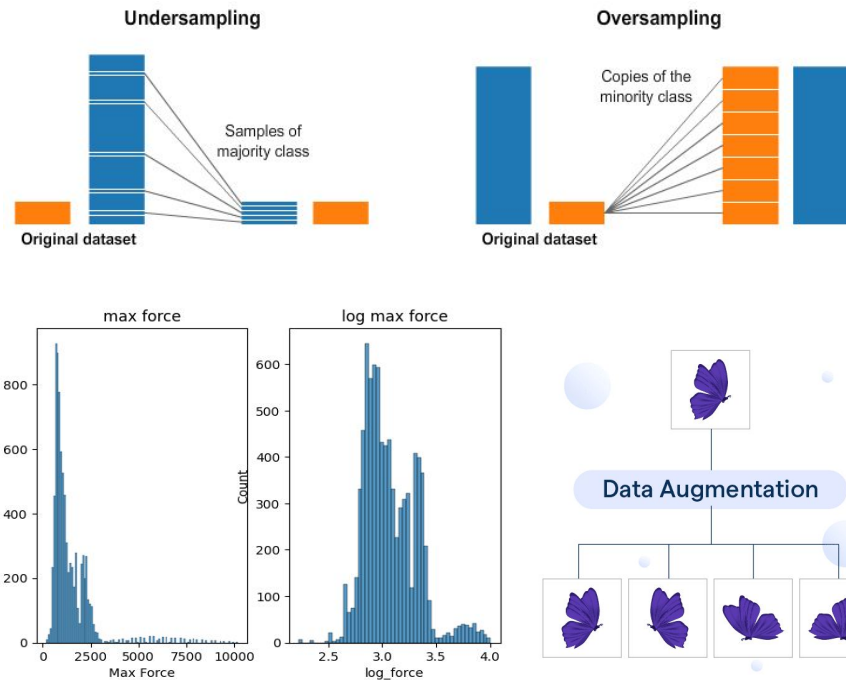
Concept Gen: Customization

Sub-function requirements:

- Stable prediction deviation for various types of box with various width, length and height
- Stable prediction deviation ratio at different max-force points
- Model's ability to capture symmetry of the environment condition

Generated Ideas:

- Using oversampling to solve imbalance training data distribution
- Finding a bijective mapping to map the data points to a uniformly or normally distributed space
- Augmenting data with spatial symmetry, enabling the model to learn symmetry conditions while enlarging the training dataset



Concept Gen: Reliability

Sub-function requirements:

- Stable converging performance during model training for multiple times
- Acceptable variance of MSE loss on multiple validation sets
- Reliability above 99.9% when dealing with extremely large or small inputs

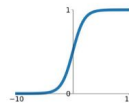
Generated Ideas:

- Use less complex model and more smooth activation functions to prevent extreme values during gradient descent
- Anomaly detection of input based on the data distribution before inference, along with exception handle module to warn the user

Activation Functions

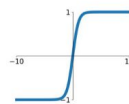
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



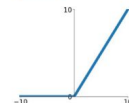
tanh

$$\tanh(x)$$



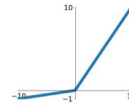
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

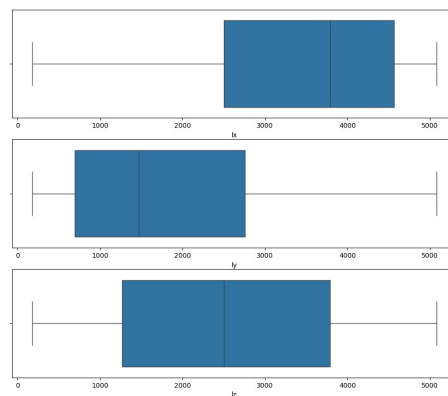
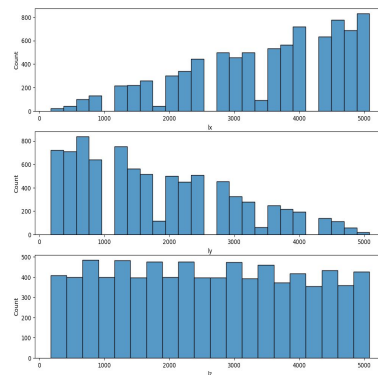
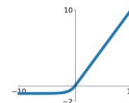


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Concept Selection: Model Introduction

Model A: DNN with GPU acceleration,

Augment data with spatial symmetry,

Anomaly detection and exception handling.

Model B: SVM,

Use oversampling,

Employ simpler models and smoother activation functions

Model C: Decision Boosting Trees,

Parallel computing,

Find bijective mapping,

Use simpler models and smoother activation functions.

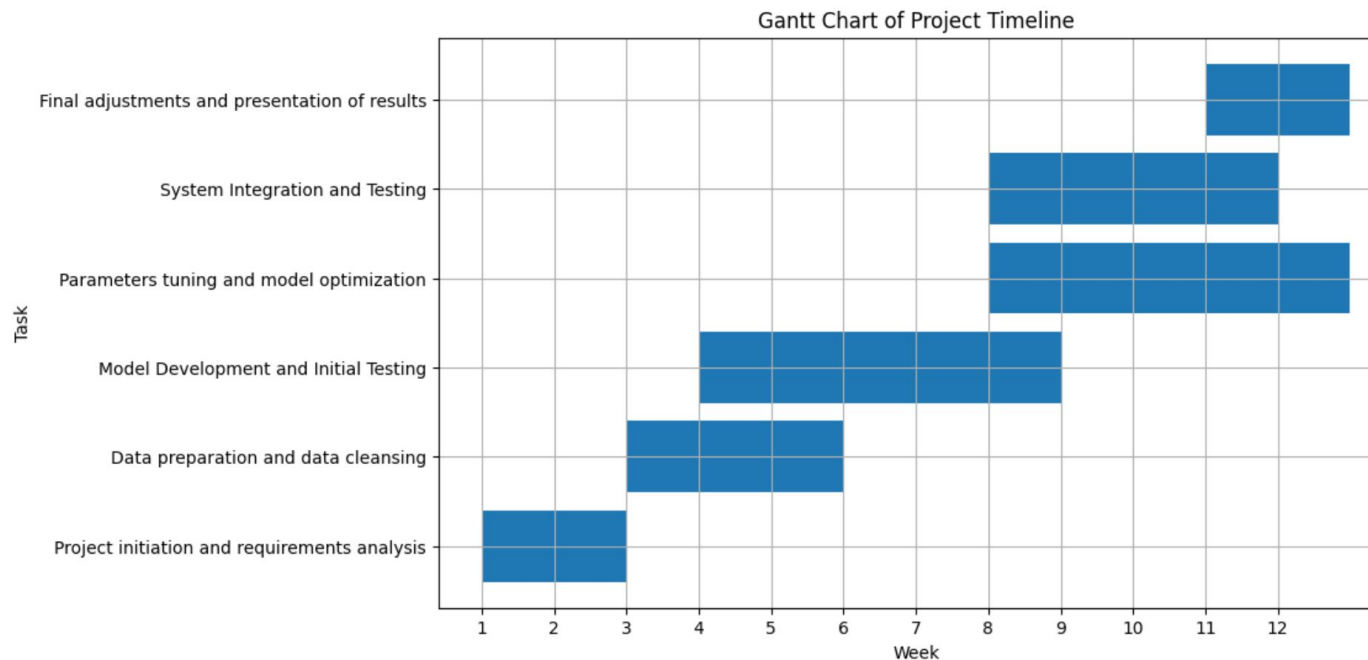


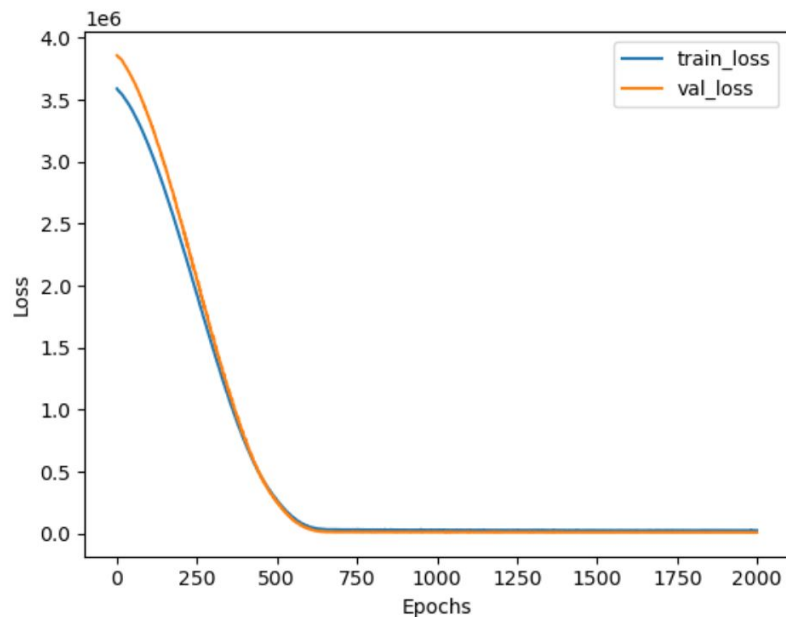
Concept Selection: Selection Matrix

Design criterion	Weight Factor	Unit	Model A			Model B			Model C		
			Value	Score	Rating	Value	Score	Rating	Value	Score	Rating
high prediction accuracy	0.36	%	95	9	3.24	90	7	2.52	92	8	2.88
Feature Learning	0.07	Score	Good	8	0.56	Good	8	0.56	Good	7	0.49
Scalability	0.05	Score	Excellent	8	0.4	Good	6	0.3	Good	6	0.3
System Optimization	0.06	Score	Excellent	9	0.54	Good	6	0.36	Good	5	0.3
Server Reliability	0.12	%	99.9	9	1.08	99	9	1.08	90	6	0.72
User Interface Design	0.02	Score	Fair	6	0.12	Fair	6	0.12	Fair	6	0.12
Cost	0.12	¥	20	9	1.08	40	7	0.84	30	5	0.6
Speed	0.2	s	260	8	1.6	200	9	1.8	400	6	1.2
			8.62			7.58			6.61		

We chose model A: DNN with GPU acceleration,
Augment data with spatial symmetry,
Anomaly detection and exception handling.

Project Plan and Progress





Use the x,y,z values to predict
the maximum force (average
value 2500)

MSE Loss: 7800

Next Steps

Acquire More Data for Training:

Objective: To improve the model's performance and ensure it generalizes well to new data.

Optimize Model Parameters:

Objective: To further reduce the loss and enhance the model's predictive accuracy.

Prevent Overfitting:

Objective: To ensure the model performs well on unseen data.

Expand Predictive Capabilities with More Dimensions:

Objective: To predict additional properties of the boxes, such as the maximum force they can withstand at specific points and the direction of the force.



Q&A





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THANK YOU !

