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

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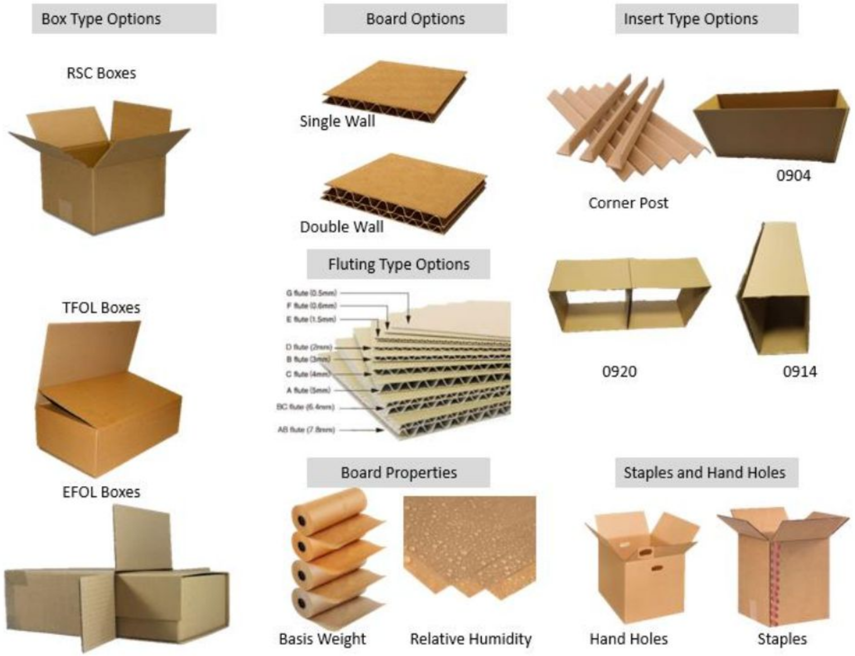
Intro: Background

- **Problem:** Corrugated boxes are often prone to buckling during storage and shipment, leading to damage and losses

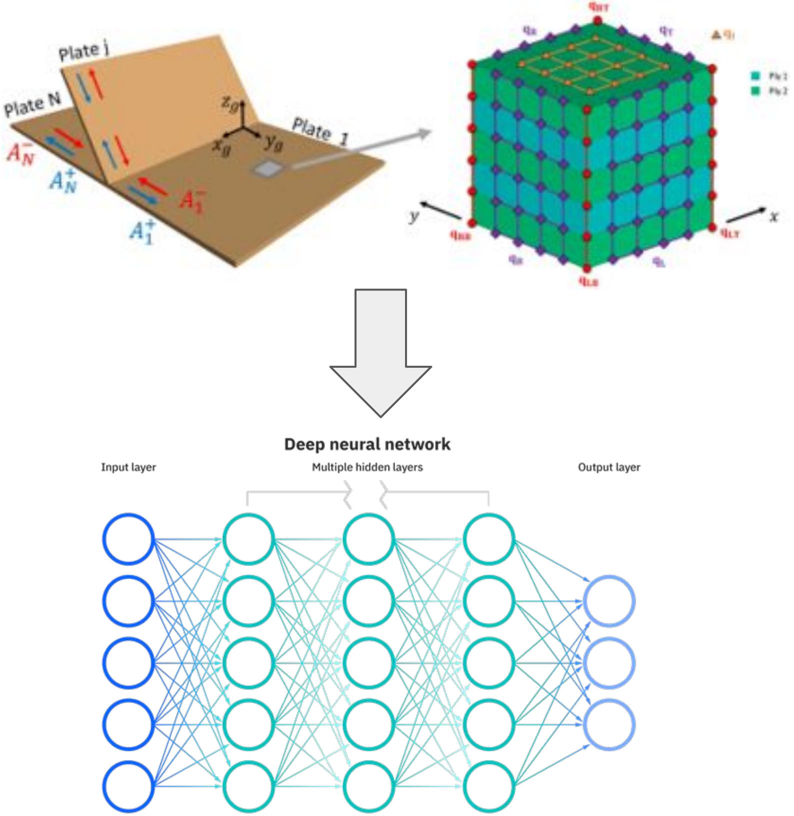
- **Current solution:** Dr. Box Calculator Pro relies on Finite Element Analysis (FEA) to predict how a product reacts to real-world forces. However, FEA is time-consuming and demands extensive computational resources.



Intro: Background

- **Proposed solution:** Replacing FEA in the Dr. Box Calculator Pro with Deep Neural Networks (DNN).

- **Expected outcomes:** A predictor interface with improved accuracy, speed and lower inference cost under various conditions and box types.



Customer requirements

- **Good Simulation**: High-quality predictions that accurately reflect real-world outcomes.
- **Very Fast**: The system should deliver results rapidly to enable efficient decision-making.
- **Can Accept Various Inputs**: The system must be capable of handling diverse input variables to accommodate different user needs.
- **Very Reliable**: The system needs to operate with high reliability and minimal downtime.
- **User-Friendly**: The interface should be easy to use for all user levels, ensuring a low learning curve.
- **Inexpensive**: The solution should be cost-effective for the user.

QFD Digram

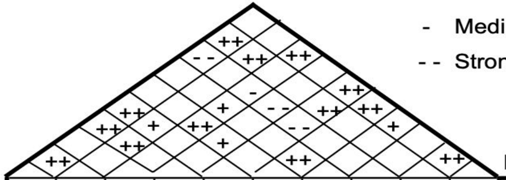
Correlation between eng. S

++ Strong Positive

\+ Medium Positive

\- Medium Negative

\- - Strong Negative



	Weight (1-10)											Benchmarks		
		DNN Integration	Feature Learning	Scalability	End-to-End Learning	System Optimization	Server Reliability	User Interface Design	Cost	Accuracy	Speed	*competitor A*	*competitor B*	
Good simulation	10	10	8		5	10	7			10		9	8	
Very fast	8	8	7	7	7	10		7	7		10	5	4	
Accept various inputs	8	7	6	10	8	7		7		7		10	7	
Very reliable	7	5			4	8	10		7	5	6	9	7	
User friendly	5				3	6	6	10				5	4	
Inexpensive	7	7		5		10	8	8	10	6	7	5	4	
Measurement Unit		MSE	Scor	GB	h	LOP	%	Scor	¥	%	s			
Target Value							99	20		90	300			
Total		304	184	171	213	392	226	218	175	233	171			
Normalized		0.13	0.08	0.07	0.09	0.17	0.10	0.10	0.08	0.10	0.07			

Correlation between customer reqs and eng. Specs

9 = Strong Relationship

3 = Medium Relationship

1 = Small Relationship

(blank) = Not Related

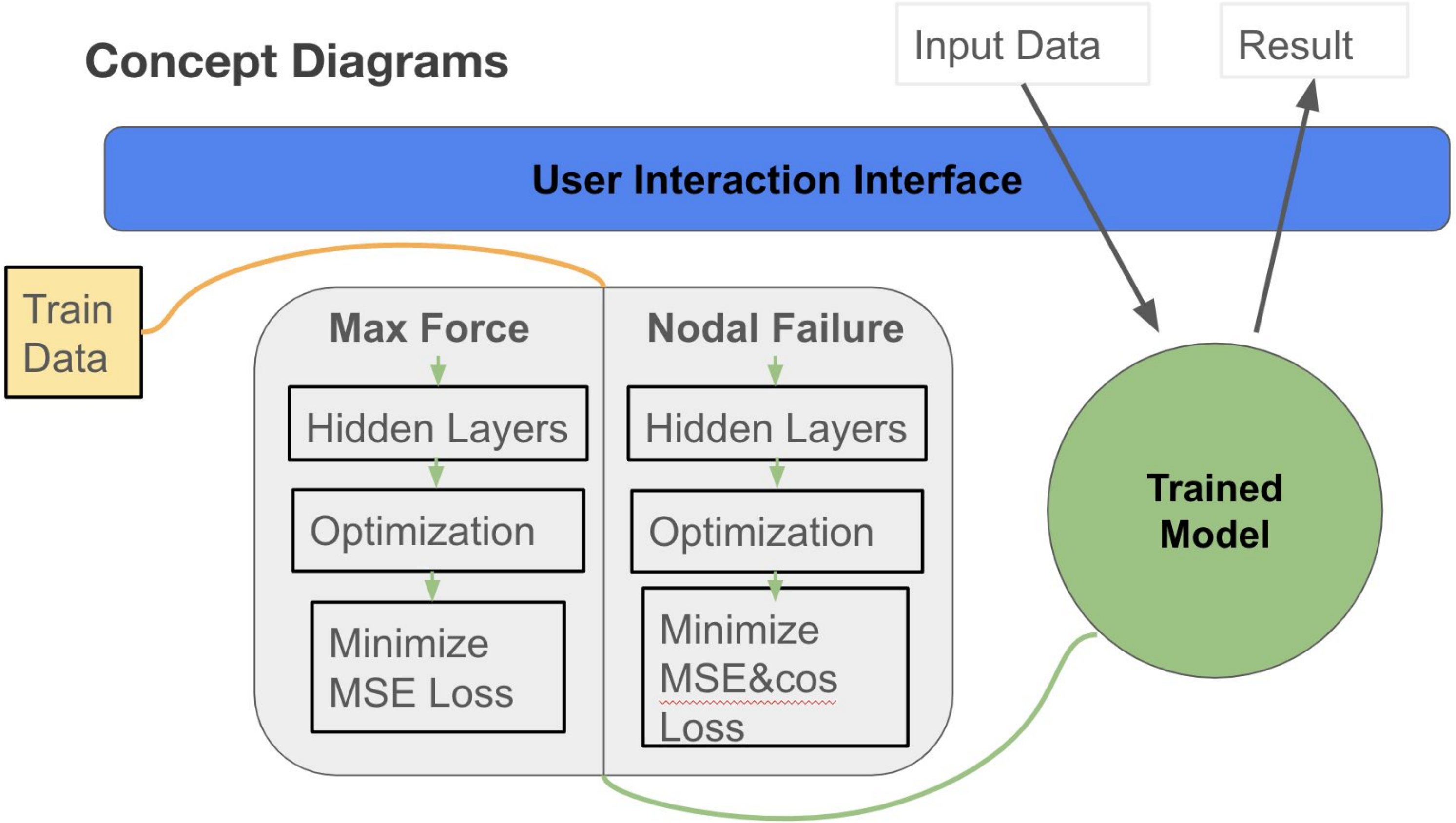
Specific Engineering Requirements

Basic idea: Current finite element based websites are used as reference.

Requirements	Specifications	Target	Measurement
Accuracy	Predictive accuracy within 90%	≥ 90% accuracy	Statistical analysis of prediction vs actual
Speed	Analysis time per simulation	≤ 5 minutes	Time tracking software
Customization	Support diverse conditions	Handle 20+ variables	System configuration checks
Reliability	System operational uptime	99.9% uptime	Server Monitoring tools

Concept Generation

Concept Diagrams



Concept Generation

- **1. Data augmentation:**

  Aim for stable prediction for different scales. However, we only have limited trainable data. (a. Oversampling; b. Customized loss function; c. data symmetry augmentation…)

- **2. Activation Function:**

  Ensure stable converging performance during repetitive model training session. (a. LeakyRelu; b. Gaussian Error Linear Unit; c. Hyperbolic Tangent…)

- **3. Dimension Reduction:**

  Deal with high-dimensional data outputs (128 dimension vector for each output of six target), dimension reduction becomes essential. (a. PCA; b. t-sne…)

- **4. Optimizer Selection:**

  The choice of an optimizer is integral to the training of neural networks, particularly in terms of convergence speed and the model's performance on new, unseen data. (a. AdamW; b. RMSprop; c. SGD…)

Concept Selection

Function	Options	Advantages	Disadvantages
Data Augmentation	• Oversampling • Customized Loss Function • Data Augmentation with x-y spatial symmetry	• Balances training data distribution • Increases importance of minority data • Enhances model's understanding of spatial symmetry	• May introduce bias • Could overfit on minority samples • May not generalize well beyond trained symmetries
Activation Function	• More complex models • Smoother functions like ReLU • Anomaly detection with exception handling	• Prevents extreme values • Stable performance • Warns users of anomalies	• May limit model capacity • Simple functions may not capture complex patterns • Additional computational overhead
Dimension Reduction	• PCA • t-SNE	• Simplifies high-dimensional data • Preserves global data structure	• t-SNE may not scale well with larger datasets • PCA assumes linearity
Optimizer Selection	• SGD • RMSprop • AdamW	• Adapts learning rate • Efficient learning and generalization	• SGD may converge slowly • RMSprop might not perform well on non-stationary problems • AdamW could lead to overfitting in some cases

Selection matrix

- **Model A**:
  - Data Augmentation with x-y spatial symmetry
  - Smoother Functions like ReLU and Anomaly Detection with Exception Handling
  - PCA Dimension Reduction Method
  - AdamW Optimizer

Final Design

Overview:

- **Goal**: Enhance buckling strength prediction for corrugated paper boxes.
- **Method**: Integrate neural networks into a user friendly interface.

DNN Integration:

- Trained on historical box performance data
- Recognizes complex relationships and patterns affecting box performance

User Interface:

- Simple and user-friendly design
- Easy input of box specifications and rapid output of predictions

DNN Model Design and Optimization

Model Design:

- Training Dataset: Historical data of various box specifications and their performance outcomes
- Specific hidden layers for different prediction tasks (e.g., max force prediction and nodal failure prediction)

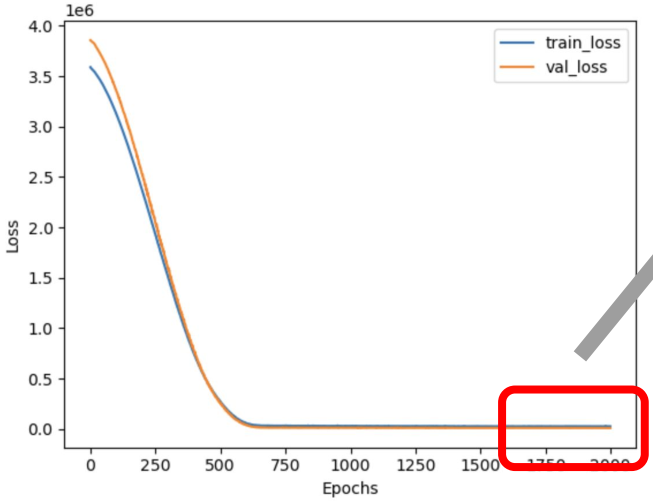
Optimization Algorithms:

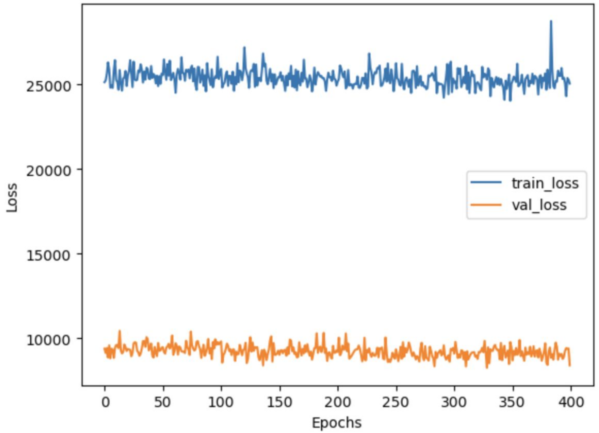
- Parameter adjustment methods
- Loss Functions: Minimizing Mean Squared Error (MSE) and cosine similarity loss for accuracy improvement

Final design/methodology description

Max Force Prediction:

- Data Preprocessing
  - Augmentation
- Model Definition and Training
  - linear, ReLU, BatchNorm1d, and Dropout layers
  - Adam optimizer
  - MSE loss
- Model Evaluation
- Final Results





Last 400 Epochs v.s. Loss

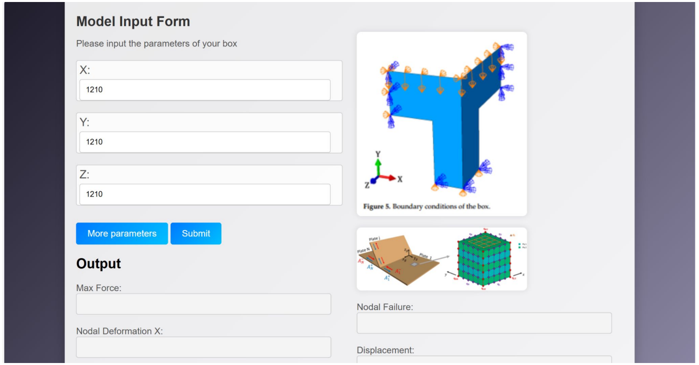
User Interface and System Output

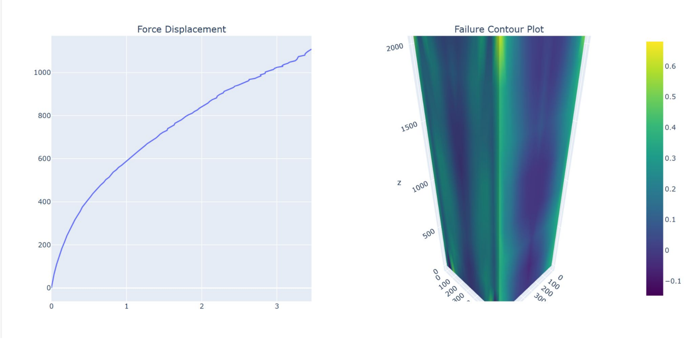
User Interface Design:

- User input parameters: box specifications, material type, expected load conditions
- Intuitive and user-friendly design for accurate data capture

System Output:

- Output results: maximum load capacity and potential nodal failure points
- Results presentation in an accessible format for easy decision-making





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Prototype Description

Test Results

Evaluation of our numerical results:

	MF	Nx	Ny	Nz	NF	Displacement	Force
(Length) Precision	93%	92%	95%	88%	95%	70%	85%
Cosine Similarity	NA	99%	99%	99%	90%	99%	99%

Evaluation of our costs:

Cost Analysis	Our method	Original FEA method
Time	10ms	30s
Computational Resources	1 core	600 cores

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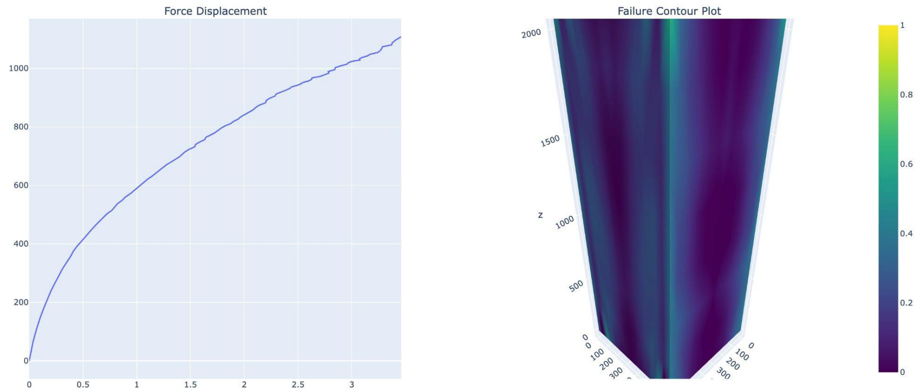
Discussion

Design Choices Reflection

- **Rapid prediction:** two seconds per input.
- **High cosine similarity accuracy:** above 99%.
- Interactive 3D rendered box diagram.



Areas for Improvement

- Enhance precision for Displacement and Force outputs which fell below the expected 90% accuracy threshold.
- Address the unexpected increase in input dimensions impacting model complexity and training efficacy.

Conclusion

Project Summary

- Integrating DNN to replace traditional FEA.
- Improved prediction accuracy and computational efficiency, significantly enhancing real-time application feasibility.

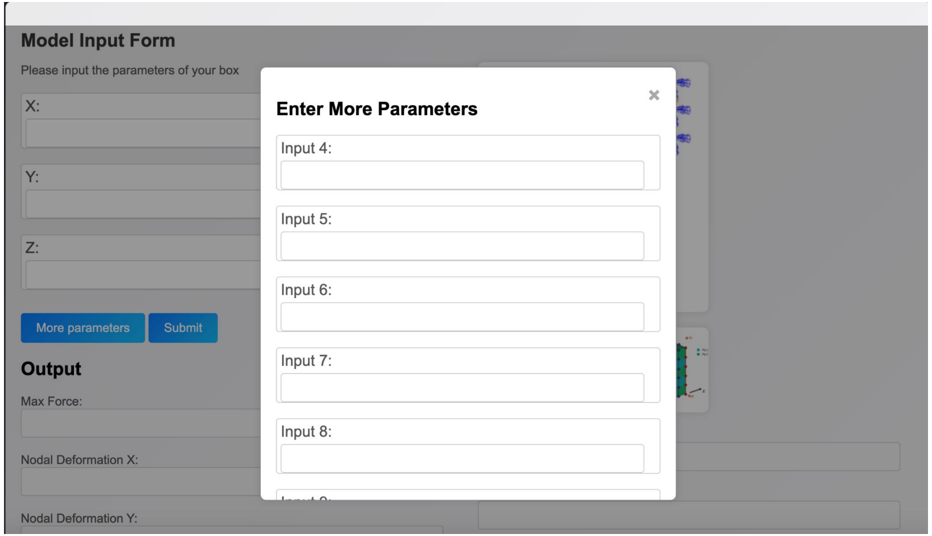
Solution Impact

- DNN integration facilitates instant buckling strength predictions and substantial reductions in computational costs.
- Potential alternative solution to multi-type box FEA replacements.

Future Works

Model Enhancements

- More nuanced loss function.
- More complex models.



Training and Data Handling

- Explore advanced data augmentation.
- Integrate additional algorithms from FEA to refine the DNN's predictive accuracy.
- A classifier before the DNN when encountering more complex situations.

Q&A

THANK YOU ！