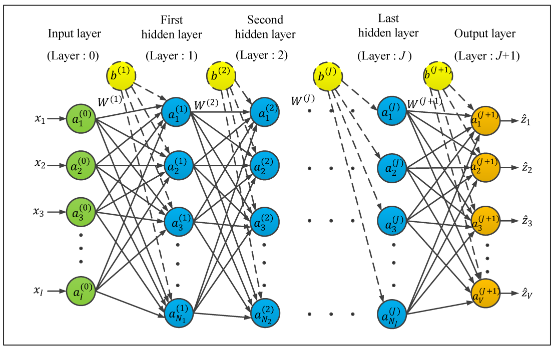
UM-SJTU JOINT INSTITUTE
Major Design Experience

Design Review 1: Report

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



Instructed by

Dr. Jigang Wu

Sponsored by

Dr. Shane Johnson, Associate Professor of UM-SJTU JI

August 12, 2024

Name	Email
Yanzhuo Cao	yanzhuo@umich.edu
Fengyu Zhang	zhangfengyu@umich.edu
Keye Chen	keyechen@umich.edu
Shuo Deng	denso@umich.edu

Abstract

This project tackles a critical issue in the packaging and delivery industry, focusing on structural behaviors of corrugated paper boxes. Although these boxes are widely used because of their lightweight, recyclable, and customizable properties, they are prone to buckling during storage and shipment, resulting in product damage, lost revenue, wasted resources, and customer complaints.

Currently, the industry relies on the Dr. Box Calculator Pro, which employs Finite Element Analysis (FEA) to predict box performance under various conditions. While effective, FEA is time-consuming and demands significant computational resources. To address these limitations, we propose integrating Deep Neural Networks (DNN) into the Dr. Box Calculator Pro to replace part of the FEA calculation. DNN's ability to model complex non-linear relationships through multiple layers offers advantages such as automatic feature learning, scalability, and end-to-end learning, making them well-suited for big data applications.

Our solution aims to provide instant predictions of buckling strength, reduce computational costs, and efficiently handle diverse box types and conditions. The expected outcome is enhanced prediction accuracy, faster analysis, and overall improved efficiency in packaging and logistics operations. The primary challenge is achieving accurate and efficient predictions of buckling strength, with specifications including high predictive accuracy ($\geq$ 90%), fast analysis rate ($\leq$ 5 minutes per simulation), the ability to handle various box configurations, and system reliability above 99.9% in practice.

The project plan is methodically structured. In the initial two weeks, the project will commence with requirement analysis, followed by two weeks of data preparation and cleansing. The subsequent four weeks will focus on developing and initially training the DNN model. The final five weeks will involve optimizing the DNN model, integrating it with the Dr. Box Calculator Pro, conducting system testing, and validating it against traditional FEA methods.

The integration of DNNs is anticipated to revolutionize the packaging industry by offering faster, more accurate, and scalable predictions of buckling strength. This advancement will reduce operational costs and enhance customer satisfaction by minimizing product damage during transit. The motivation behind this project is to apply modern machine learning techniques to solve long-standing industry problems, improving the efficiency and effectiveness of packaging and logistics operations.

Contents

1 Introduction

1.1 Background

Our project addresses critical challenges in the packaging and logistics industry, particularly concerning corrugated paper boxes. These boxes are extensively used due to their lightweight, recyclable, and customizable properties. However, they are prone to buckling during storage and shipment, leading to product damage, revenue loss, wasted resources, and customer complaints.

The current solution to this problem is the Dr. Box Calculator Pro, a website that provides users with an interface to predict the performance of corrugated boxes using Finite Element Analysis (FEA). FEA is a numerical method for predicting how a product reacts to real-world forces, vibrations, heat, and other physical effects by dividing a complex problem into smaller, simpler parts (finite elements) and solving them. Despite its effectiveness, FEA is time-consuming and demands extensive computational resources.

Our proposed solution involves replacing FEA with Deep Neural Networks (DNN) in the Dr. Box Calculator Pro. DNNs are artificial neural networks with multiple layers between the input and output layers, allowing them to model complex non-linear relationships. DNNs offer several advantages, including automatic feature learning from raw data, scalability to handle large-scale data and complex models, and the capability for end-to-end learning, which simplifies the prediction pipeline.

Our expected outcomes are improved accuracy, speed and lower inference cost. By incorporating DNNs into the Dr. Box Calculator Pro, we can achieve instant predictions of buckling strength, significantly reduce computational costs, and expedite analysis. Additionally, DNNs can handle diverse box types and conditions, enhancing the efficiency and effectiveness of packaging and logistics operations.

1.2 Literature Review

1.2.1 Traditional Finite Element Analysis (FEA) Approaches

Finite Element Analysis (FEA) has been extensively used to predict the buckling strength of corrugated cardboard boxes, offering a robust and accurate method for such analyses. For instance, Fehér et al. (2023) analyzed the compressive strength of corrugated paperboard packages with different cutout rates using FEA. Their study, which employed a homogenized linear elastic orthotropic material model with Hill plasticity and modeled only one-eighth of the box to simplify analysis, demonstrated high accuracy in predicting compression force from Box Compression Tests (BCT) despite a slight decrease in accuracy at higher cutout rates.

Traditional methods for analyzing the strength and failure of corrugated boxes include experiments, analytical models, and computational software. However, these methods require extensive experimentation and are often limited to specific box types and loading conditions. For example, analytical models like the McKee equation are limited to vertically loaded regular slotted containers (RSC).

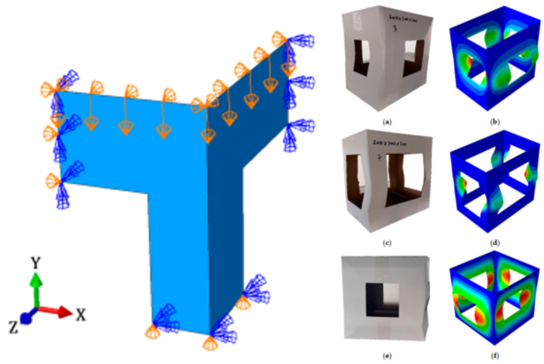


Figure 1: Numerical Analysis of FEA by Fehér et al. (2023)

1.2.2 Integration of Artificial Neural Networks (ANN) with FEA

A significant advancement in predictive modeling involves integrating Artificial Neural Networks (ANN) with FEA. This approach has been explored to improve prediction accuracy and computational efficiency, as evidenced by study of Hajializadeh and Ince (2021) on predicting residual stresses in AISI 304 L parts created through the Direct Metal Deposition (DMD) process. Their innovative model integrated ANN with FEA, focusing on the thermal and mechanical response of materials. The ANN was trained using datasets generated from FE simulations, including spatial coordinates and temperature history, to predict residual stresses. This method not only enhanced prediction accuracy but also significantly reduced computational time.

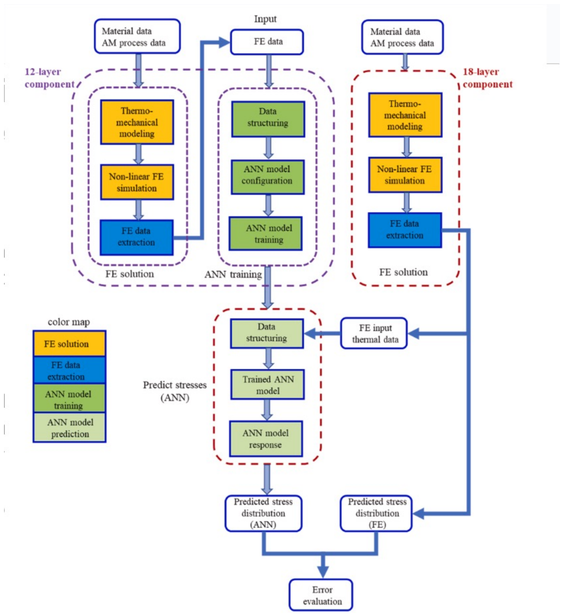


Figure 2: Training Process for DMD

The novel aspect of integrating ANN with FEA lies in its ability to handle complex data relationships more effectively than traditional methods. This integration allows for quicker evaluations and can be adapted to different box types and materials, providing a flexible and scalable solution for packaging analysis.

1.2.3 Comparison and Novelty of the Proposed Design

In comparison to the aforementioned studies, our proposed design integrates the strengths of both traditional FEA and ANN to provide a comprehensive and efficient analysis tool for corrugated cardboard boxes. Unlike the study by Fehér et al. (2023), which solely relied on FEA, and the work of Hajializadeh and Ince (2021), which focused on metal materials, our design applies ANN-enhanced FEA specifically to corrugated cardboard boxes. This approach addresses the limitations of traditional methods by improving prediction accuracy and reducing computational time, making it suitable for a wider range of packaging solutions.

The novelty of our design lies in its ability to predict box performance based on paper properties for various box types and designs, including special features like hand holds and ventilation holes. Moreover, in contrast, our model is further designed for multi-task labeling, which includes nodal Deformation x, nodal Deformation y, nodal Deformation z, nodal Failure, displacement and force. Each dimension has more 128 outputs to generate. It also shows a broader application in the physical field.

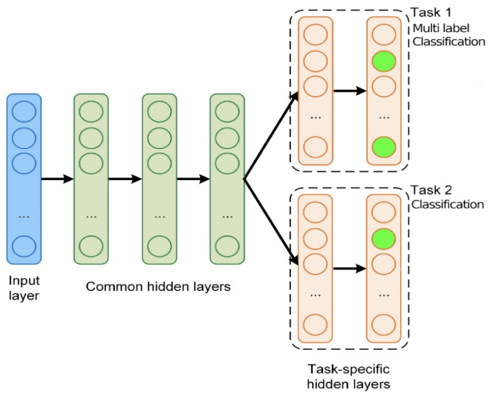


Figure 3: Multi-task Predictions

This hybrid approach combines the accuracy of FEA with the efficiency of ANN, enabling non-specialized personnel to conduct robust and cost-effective packaging analyses.

2 Customer Requirements and Engineering Specifications

2.1 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.

2.2 Process to Determine Engineering Targets

- **Good Simulation (Accuracy, Feature Learning, End-to-End Learning)**
  - *Requirement Translation*: Convert the need for "high-quality predictions" into a specific accuracy metric.
  - *Specification*: Achieve at least 90% accuracy in simulation predictions.
  - *Metric*: Use confusion matrices, ROC curves, and precision-recall metrics from validation datasets to measure.
  - *Process*: Involve feature learning capabilities in the DNN to automatically discern and utilize the most impactful features from input data, enhancing prediction accuracy through deep learning techniques.
- **Very Fast (Speed, System Optimization)**
  - *Requirement Translation*: Define what "deliver results rapidly" means in a measurable time frame.
  - *Specification*: Reduce simulation time to under 5 minutes per run.
  - *Metric*: Implement benchmarking tests to track and verify the response times across various operations within the system.
  - *Process*: Optimize the computational efficiency of the DNN model by refining algorithmic approaches and utilizing efficient computing resources.
- **Can Accept Various Inputs (Scalability)**
  - *Requirement Translation*: Specify the types and variety of inputs the system should handle.
  - *Specification*: Support at least 20 distinct types of input variables.
  - *Metric*: Test the system's ability to process and accurately analyze different data types and sources.
  - *Process*: Design the system architecture to be modular, allowing easy integration of new input variables without significant modifications.

- **Very Reliable (Server Reliability, System Optimization)**
  - *Requirement Translation*: Translate the need for high reliability into specific uptime and redundancy requirements.
  - *Specification*: Achieve 99.9% system uptime.
  - *Metric*: Use server monitoring tools to track uptime and automatically detect and resolve potential downtimes.
  - *Process*: Implement fault tolerance mechanisms such as redundancy and regular maintenance checks to ensure consistent performance.
- **User-Friendly (User Interface Design)**
  - *Requirement Translation*: Define what makes the interface "easy to use".
  - *Specification*: Achieve a user satisfaction rating of at least 80% on usability.
  - *Metric*: Conduct user testing sessions and gather feedback to assess the intuitiveness of the interface.
  - *Process*: Apply principles of user-centered design during the development phase to ensure the interface is intuitive and accessible to all user levels.
- **Inexpensive (Cost)**
  - *Requirement Translation*: Quantify what "cost-effective" means in comparison to competing solutions.
  - *Specification*: Keep the cost per simulation below a competitive benchmark, say 20% less than similar services.
  - *Metric*: Regularly review cost structures and market prices to ensure competitiveness.
  - *Process*: Streamline operations and utilize cost-effective technologies and methodologies to reduce overheads and pass these savings on to users.

2.3 Quality Function Deployment (QFD) and Specific Engineering Requirements

2.3.1 QFD

Based on the above translation process, we finally obtained the QFD diagram as below.

Quality Function Development (QFD)

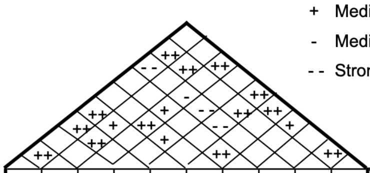
Correlation between eng. S

++ Strong Positive

\+ Medium Positive

\- Medium Negative

\- - Strong Negative



Benchmarks

	Weight (1-10)	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			
competitor A														
competitor B														

Correlation between customer reqs and eng. Specs

9 = Strong Relationship

3 = Medium Relationship

1 = Small Relationship

(blank) = Not Related

Figure 4: QFD Diagram

2.3.2 Specific Engineering Requirements

After a detailed discussion with the customer, we made another table of specific engineering requirements as below.

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

Figure 5: Table of Specific Engineering Requirements

3 Project Plan

- In the first two weeks, we will be initiating the project and analyzing requirements, which we have almost completed.
- Moving into weeks three, we will concentrate on preparing the necessary data and conducting data cleansing. We will clean and preprocess this data to ensure it is of high quality, ready for use in our model development.
- From week four, we will start developing the initial Deep Neural Network model. After the initial construction of the modeling framework, we will train this model using the data we have prepared. We will also conduct preliminary tests to evaluate the model's performance and accuracy. Based on these tests, we will try to adjust model parameters to optimize performance.
- From week eight till the end of the project, we will continue to focus on further optimizing the DNN model, which involves tuning hyperparameters and using cross-validation techniques to enhance model accuracy. If possible, we will compare its performance with that of the traditional FEA model to validate our model's effectiveness.
- At the same time, we will try to integrate our DNN model into the DrBoxOnline.com platform. We will perform some system integration tests to ensure compatibility between the model and the platform.

- Finally, in week twelve, we will summarize our project outcomes and showcase our progress and achievements to stakeholders.

4 Conclusions

This project aims to address the critical issue of buckling in corrugated paper boxes within the packaging and logistics industry by integrating Deep Neural Networks (DNN) into the Dr. Box Calculator Pro, replacing the traditional Finite Element Analysis (FEA) method. The proposed solution leverages the advanced capabilities of DNNs to model complex non-linear relationships, offering significant improvements in prediction accuracy, computational speed, and cost-effectiveness.

Through our comprehensive project plan, we have structured the development process into distinct phases: requirement analysis, data preparation and cleansing, initial DNN model development and training, optimization of the DNN model, system integration, and final validation. Each phase is meticulously designed to ensure the successful implementation and integration of the DNN model into the existing system, aiming for high predictive accuracy, rapid analysis, and system reliability.

The anticipated outcome of this project is a revolutionary tool that will provide instant predictions of buckling strength, reduce computational costs, and handle diverse box types and conditions with high reliability and user-friendliness. This advancement is expected to enhance the efficiency and effectiveness of packaging and logistics operations, ultimately leading to reduced operational costs and improved customer satisfaction by minimizing product damage during transit.

In conclusion, by applying modern machine learning techniques to solve long-standing industry problems, our project not only aims to improve the performance and reliability of the Dr. Box Calculator Pro but also to set a new standard in the packaging industry for predictive analysis and operational efficiency.

References

Fehér, L., Mrówczyński, D., Pidl, R., and Böröcz, P. (2023). Compressive strength of corrugated paperboard packages with low and high cutout rates:

Numerical modelling and experimental validation. *Materials*, 16(6):2360. Accessed: 2023-03-15.

Hajializadeh, F. and Ince, A. (2021). Integration of artificial neural network with finite element analysis for residual stress prediction of direct metal deposition process. *Materials Today Communications*, 27:102197.

5 Biographical Sketch

5.1 Yanzhuo Cao

5.1.1 Future Plans

Study Plan: After graduation from UM-SJTU Joint Institute, I will need to go back to the School of Information, University of Michigan to complete the Global Degree Program. If Everything Goes Well, I will gain a master degree of Big Data Analytic in May, 2025.

Work Plan: After graduation from University of Michigan, I decided to go back to China and find an internet company to work. My job preferences will be in algorithm and data fields rather than development fields since I am really poor at the basic data structure hahaha.

Life Plan: I have a lot of hobbies, and in near future, I would like to read as many politic books as possible since I really think that very important political events will happen in 5 years. Therefore, I will need to get prepared. Besides, I have decided to lose weight – I am 5 kilograms heavier than freshman year /cry.

5.1.2 Self Picture

Figure 6: Yanzhuo Cao

5.2 Fengyu Zhang

5.2.1 Future Plans:

- I am Fengyu Zhang, currently pursuing a Master's degree in Information Science at the University of Michigan. Concurrently, I am completing my senior year in Electrical and Computer Engineering at the Joint Institute (JI), where my academic pursuits are deeply intertwined with my passion for machine learning, including areas such as traditional supervised learning, deep learning, and natural language processing. My aim is to utilize my knowledge to significantly contribute to my team and achieve a successful outcome in our capstone design project.

- In addition to my academic endeavors, I am an intern at a leading technology and e-commerce company. This role provides me with a profound insight into the practical applications of AI in the industry, nurturing my aspiration to one day excel as an algorithm engineer where I can actively engage in innovative AI solutions.
- Outside the realm of technology and academics, I have a profound love for music and am dedicated to mastering the guitar. I believe that music not only enhances my creative expression but also provides a balance to my rigorous academic and professional schedule. Furthermore, I am committed to bodybuilding, which I find essential for maintaining both physical and mental wellness.

5.2.2 Self Picture

Figure 7: Fengyu Zhang

5.3 Keye Chen

5.3.1 Future Plans

Study Plan: After graduation from UM-SJTU Joint Institute in this August, I will need to go back to the School of Information, University of Michigan to complete my master's degree in Big Data Analytics. If Everything Goes Well, I will gain a master's degree in May, 2025.

Work Plan: After graduation from University of Michigan, I decided to go back to China and find a job relevant to Information Technology. Since it would be a really tough experience working in a routine of 996, I will consider pursuing another degree or switching to a more relaxing job after several years.

Life Plan: I am devoted to traveling around the world with my cameras, and drones. I love the photograph and natural scenery! Additionally, I keep a hobby in the gym and I believe that adequate body training can make me always in a positive mode.

5.3.2 Self Picture

Figure 8: Keye Chen

5.4 Shuo Deng

5.4.1 Future Plans

Study Plan: After graduation from UM-SJTU Joint Institute in this August, I will need to go back to the School of Information, University of Michigan to complete my master's degree in Big Data Analytics. If Everything Goes Well, I will gain a master's degree in May, 2025.

Work Plan: After graduation from University of Michigan, I may go back to China and find a job relevant to AI agent and LLM. I'd like to spend several years to participate in the information technology to see how far AI can go.

Life Plan: I am interested in digital painting and my dream is to express the world with my own interpretation. I want to practice more while traveling around during my leisure time.

5.4.2 Self Picture

Figure 9: Shuo Deng

5.5 Yukuan Zhu

5.5.1 Future Plans

Study Plan: After graduation from UM-SJTU Joint Institute in this August, I will need to go back to the School of Information, University of Michigan to complete my master's degree in Big Data Analytics. If Everything Goes Well, I will gain a master's degree in May, 2025.

Work Plan: After graduating from the University of Michigan, I plan to return to China and work for a technology company, maybe working in NLP. If I will be able to earn enough before 40, I plan to become a high school or junior high school teacher after that.

Life Plan: My biggest hobby is traveling. I like to go to scenic places with my friends and then record the beauty with my camera. This is also the reason why I want to become a teacher after 40. I want to travel around the world during summer and winter vacation time.

5.5.2 Self Picture

Figure 10: Yukuan Zhu