# Art Meets Technology: The Birth of Ori(go)

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## ABSTRACT

**Ori(go) is an innovative startup idea I conceived in the Fall of 2023, centered around a digital origami database. The database contains intricate personally collected origami structures and features a wide range of aesthetic model designs and animations, based on user preferences. In essence, users upload photos of their own origami paper creations, and an advanced AI system will identify and evaluate the model before generating then replicating the digital animated version. Initially, I envisioned this project to support childhood development within educational sectors because origami, a cherished and timeless art form, can offer children the opportunity to express their creativity through hands-on experience at a young age, fostering the development of key skills that will be invaluable for their future.**

**With Ori(go) this year, I have created a convolutional neural network (designed for image classification tasks) to accurately predict origami structures, achieving a notable accuracy (0.71) and recall rate (0.68). After conducting ad hoc analysis on the origami data, I evaluated its distribution, which appeared to be right-skewed—indicating that most origami structures were categorized as easy or moderate in difficulty. I then built a simple regression model to examine the impact of fold times on the perceived difficulty of each origami model. I later concluded how fold times relate to the difficulty of an origami model and charted a new adjusted difficulty score based on weights in regard to fold time (w1) and fold count (w2).**

**As a part of Ori(go)'s ongoing evolution and future development, users will soon have the opportunity to earn points and gain access to exclusive animations and designs, adding even more depth to their digital experience. Once users have crafted the corresponding origami model in real life and uploaded a photo, they can use a digital currency (Org) to enhance their creations with unique animations and designs. Additionally, users can also challenge their friends by competing to see who can complete an origami design the fastest and achieve the highest complexity score, as determined by an advanced AI system.**

Keywords: CNN, Linear and Polynomial Regression, CatBoost, LightBoost, XGBoost, Decision Trees, SHAP Values, Classification Model, Density Distribution Plot, Epoch Selection, Precision, Recall, R- squared, Data Science, Machine Learning, Artificial Intelligence, Predictive Modeling, Feature Importance, Neural Networks


**Figure 1.** Ori(go) Origami on the GO

## INTRODUCTION

Origami, while frequently overlooked yet complex, is profoundly rooted in mathematical principles of geometry and symmetry. After attending a seminar, "A World from a Sheet of Paper", at Dartmouth by Stanford professor Tadashi Tokieda, I was deeply inspired by the diversity and intricacy of origami puzzles and geometry. As it is well-established that origami transforms a two-dimensional object into a three-dimensional structure, I would argue that Ori(go) will rekindle these aspects of transformation and solidify an appreciation for transformative geometry in motion.

Once considered an ancient and perhaps obsolete art form, origami is now poised for revitalization through Ori(go), a platform that blends creativity with sophistication. The integration of digital innovation with Ori(go) has the power to revitalize origami, making it more accessible and relevant in today's rapidly evolving world.

### Importance

As the world increasingly shifts toward a digital landscape, the relevance of origami and digital models is becoming more pronounced. While origami has been popularized by Japanese culture, its resurgence — through Ori(go) — could introduce new dimensions of learning, creativity, and engagement. For instance, according to Central Michigan University, in Hawaii, the tradition of folding origami cranes symbolizes long life, happiness, and good fortune. Moreover, the paper crane became a symbol of hope and peace through the story of Sadako Sasaki, a young Japanese girl who folded 1,000 cranes while battling leukemia. This connection between paper and hope symbolizes the deep cultural ties that origami holds.

Origami is not only a creative art form, but encompasses theraputic elements that have notable mental health benefits. Using Bandura's social learning theory (1986) and Kolb's constructivism (1984), it becomes evident that Ori(go) can emphasize the role of observation and imitation in the learning process. Just as card collecting and other hobbies promote collectivism, folding paper and building a personal collection of origami models can be a rewarding experience. The act of folding itself can be taught and learned within communities, fostering cultural ties and enhancing social connections.

From a psychological perspective, constructivism asserts that learners create knowledge through hands-on experience. In the context of Ori(go), the creation of a digital database of origami models can inspire creativity and learning. As users interact with the platform, they expand their portfolios by designing and sharing new models, further enhancing their understanding of geometry, symmetry, and spatial reasoning.

By merging traditional origami with digital innovation, Ori(go) not only preserves cultural traditions but also enriches educational experiences. The combination of art, technology, and community can make origami more relevant and engaging in today's technological world. Ori(go) thus reconceptualizes the "world from a sheet of paper "and extends its usefulness into our present digital realm, offering endless possibilities for the growth of creativity in education.

## METHODS AND MATERIALS

**Background**: Initially in the start-up process, I came across an origami simulator (origamisimulator.org) and utilized the transformative features to animate a crane origami model. I utilized the crane structure as a base model, then web developed and scraped 12 origami models from an origami database https://origami-database.com/models/ (documenting fold times, diagrams, images, names, and descriptions of structures). This provided a useful backbone which helped me ask vital questions in relation to the development of my findings. From here, I produced distribution charts to assess spread within the data, which would be useful for future potential questions I may have in mind.

**Questions:**

- How would I be able to scrape all models from the origami database in R, and how would I assess the difficulty of each structure in relation to its fold time or number of folds (regression question)?
- How much should each origami structure be worth based on its complexity, difficulty, fold patterns, fold time, number of folds, etc. (implications of AI)?

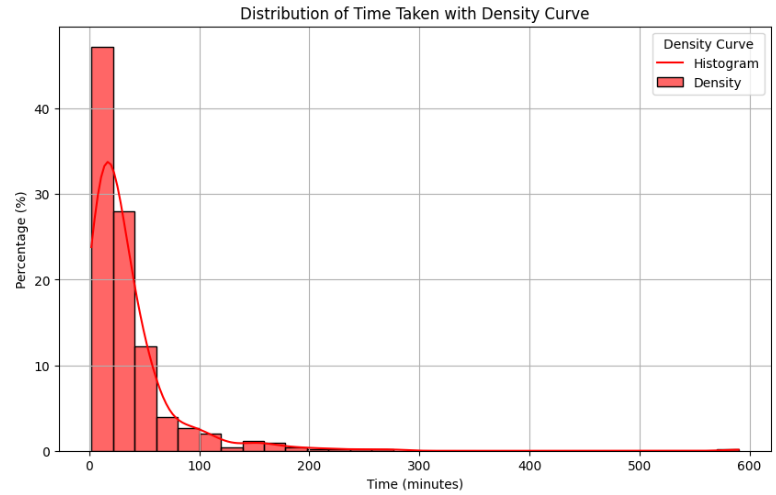


**Figure 2.** Density curve showing the distribution of origami models (most common models are either considered easy or moderate).

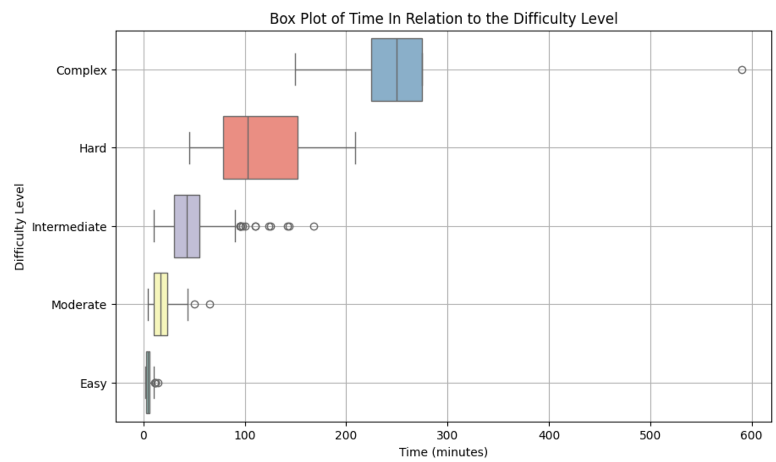


**Figure 3.** Box plots displaying the variability and distribution of origami models for each difficulty category.

- How would I be able to predict a specific type of origami structure based on its image and assign it a complexity score (classification question)?

**As these questions pertain to the conceptualization of Ori(go), my findings first had to start with the rudimentary medium itself: *paper*.**

To relate fold count to the difficulty of a model, I had to fold various origami structures and *manually* count the number of folds (Table 1) before coupling this feature with the fold time to predict a simple difficulty score. (Note: This difficulty score will become more important in the long run when considering how an AI system/ neural network will provide a complexity score that will determine the value of each origami model in the system)(value will be based on an Org - coin system that will determine the value of unique origami structures).

After folding the pieces of paper into common origami structures, I synthetically created a dataset from my findings and used that table to create an adjusted score. The provided difficulties within the origami database use a discrete 1-5 scale, but this doesn't provide enough distinction between multiple models. After creating the adjusted score, I had a clearer idea of my long-term goals.

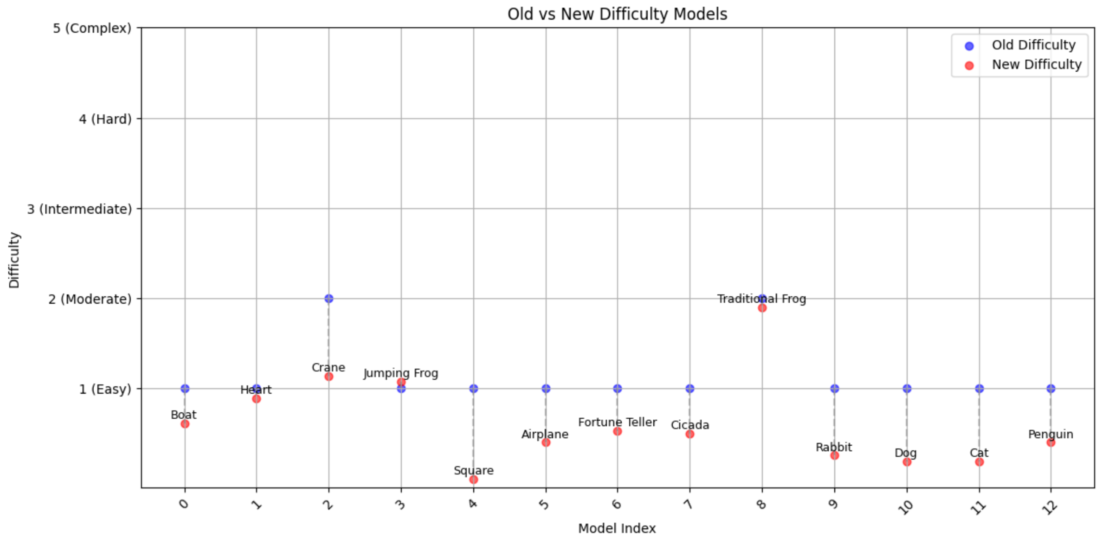


**Figure 4.** Developed an adjusted difficulty score based on the weights of fold count and fold time (standardized difficulties and eliminated discrete scale).

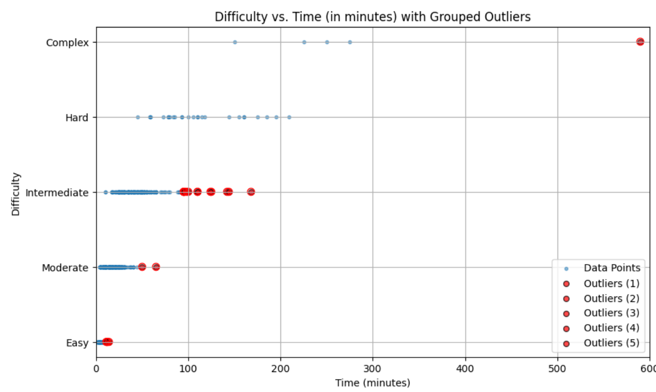


**Figure 5.** Figure documenting the removal of outliers based on distances from IQR for each unique difficulty group.

From here, I switched gears and fully scraped all 452 models from 37 pages in R using rvest and for loops, and created a simple regression model (accompanied with an r-squared score of 0.52) that revealed the innate relationship between fold time and perceived model difficulty (I only studied the relationship between time and difficulty because the fold count of all origami models was not included in the database)(This simple regression model is present in my github - https://github.com/Rxbrooks15).

After creating the regression model, I tested the dataset for outliers and excluded extreme values before creating polynomial regression models and utilizing decision trees to improve prediction scores. From here, I looked to explore further the predictive potential of regression models based on the folding times and number of folds of the model.

## 1 COMPLEXITY

In the future, the complexity of a regression model can be defined by the following equation:

$$\text{Complexity Rating} = a \cdot (\text{Number of Folds}) + b \cdot (\text{Fold type}) + c \cdot (\text{Difficulty}) + d \cdot (\text{Time }) + e \quad (1)$$

Where:

- $a$, $b$, $c$, $d$, and $e$ are coefficients learned from the data.

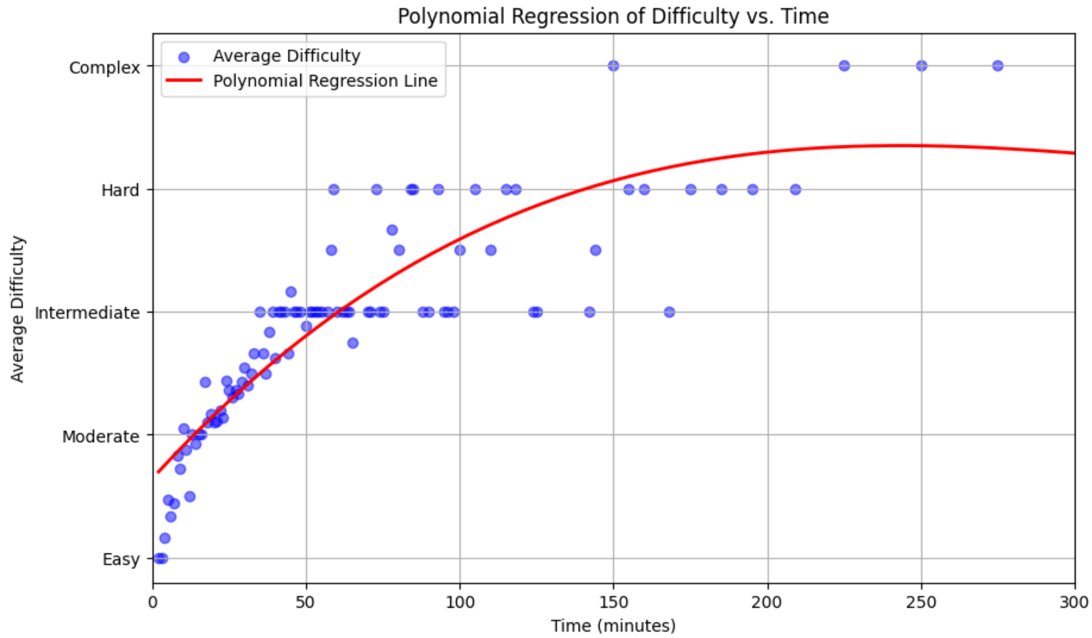


**Figure 6.** Polynomial regression fit (produced an R-squared score of 0.582); based on calculating the average difficulty of origami models made in the same amount of time (standardized difficulties and eliminated discrete scale, but fails to include all data points).

- Number of Folds: Total folds required to complete the model.
- Variety Score: Score based on the different types of folds used.
- Complexity Rating: A rating of the design complexity.
- Time : Estimated time required to complete the model.

## 2 QUESTIONS AND MACHINE LEARNING APPLICATIONS

When first comprehending the essence of Orig(go), I notice the importance of creating predictive models to assess a future complexity score. In a similar vein, I also understand the usefulness of developing an accurate classification model that determines predicted origami structures based on photographed models. These thoughts will be useful as I inquire and answer upcoming questions.

**Questions:**

- How does feature importance vary across the different models?
- How does the $R^2$ prediction vary across the models?
- Other general observations you have made at this stage.

To answer these questions, I must first capture more complex relationships between fold time and difficulty, and I will have to use these machine learning algorithms to assess this relationship:

- Decision Trees
- Random Forests
- Neural Networks
- Regression models

| Model | Number of folds | Time (m) | Difficulty |
|---|---|---|---|
| Boat | 10 | 2 | Easy |
| Heart | 13 | 4 | Easy |
| Crane | 16 | 5 | Moderate |
| Jumping Frog | 16 | 3 | Easy |
| Square | 2 | 0.5 | Easy |
| Airplane | 7 | 2 | Easy |
| Fortune Teller | 8 | 4 | Easy |
| Cicada | 8 | 3 | Easy |
| Traditional Frog | 23 | 14 | Moderate |
| Rabbit | 5 | 2 | Easy |
| Dog | 4 | 2 | Easy |
| Cat | 4 | 2 | Easy |
| Penguin | 7 | 2 | Easy |

**Table 1.** Table showing the different origami models i crafted, including their fold count, fold time, and difficulty level.

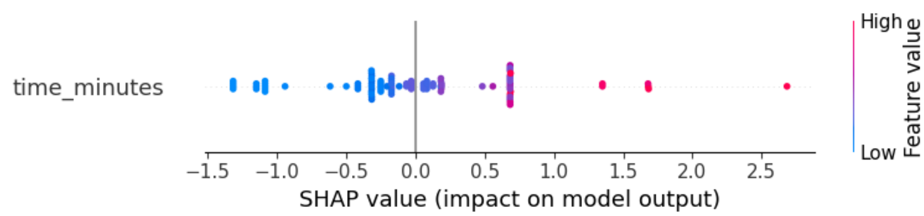


**Figure 7.** SHAP value for XGBoost model (Origami models with shorter times have less of an influence on the difficulty score).

In terms of the first question, the linear regression did not provide a traditional ”feature importance” measure like tree-based models, but for XGBoost, several metrics for feature importance were available, including:

- Gain - The improvement brought by a feature to the branches it is on.
- Cover - The relative quantity of observations concerned by a feature.
- Frequency - The number of times a feature is used in all trees.

For LightGBM, similar to XGBoost, I could analyze gain, split, and cover to determine the most impactful features. In CatBoost, feature importance is based on similar principles to XGBoost and LightGBM, but the unique advantage of CatBoost is its handling of categorical features without the need for extensive preprocessing.

For the R-squared values (in relation to the second question on page 5), Linear Regression provided a baseline R-squared score. If the relationships are linear, it can perform well; however, it seems to underperform in cases with non-linear relationships. For XGBoost, it typically exhibits higher R-squared values due to its ability to model complex, non-linear relationships through ensemble methods. LightGBM, on the other hand, often achieves high R-squared scores with faster computing speeds, making it more effective on larger datasets. Finally, CatBoost is usually expected to perform comparably to XGBoost and LightGBM, especially with categorical features.

After running several gradient boosting methods and visualizing their SHAP values (Figure 4) for the time variable, general observations I had (in regard to the last question on page 5) included the fact that LightBoost, CatBoost, and XGBoost provided differnt SHAP value visualizations. Moreover, I noted that accuracy heavily increased when going from a polynomial regression to a simple decision tree, exemplifying the strength of supervised learning regression trees (Figure 8) . **In relation to my final project question on page 3, as I created a classification model based on a Convolutional Neural**

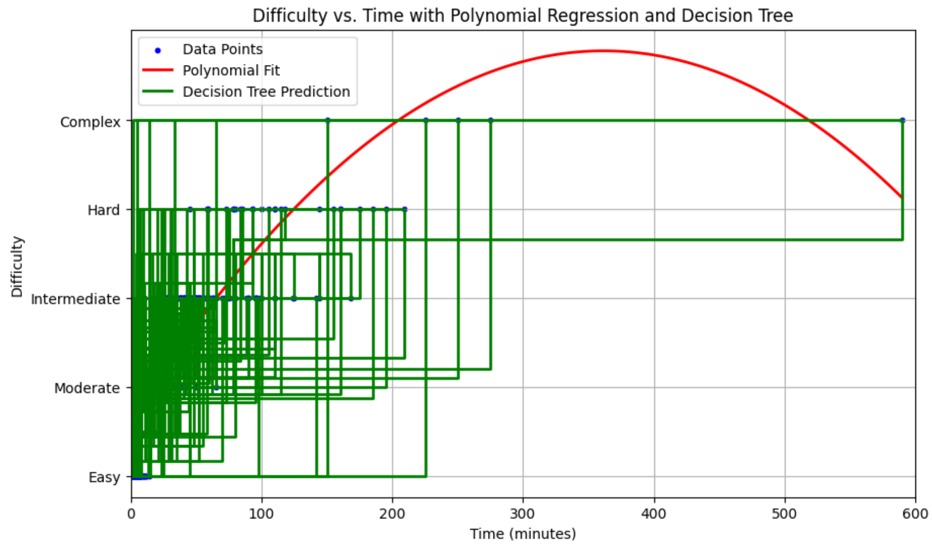


**Figure 8.** Figure documents polynomial regression fit (produced an R- squared score of 0.634) and the decision tree model ( produced an R- squared value 0.817)

**Network (CNN) to predict the names origami models from a 3000 image dataset, my CNN model highlighted the power of classification models by documenting an accuracy score of 0.71** after iterating over only 8 epochs **within a 3-hour period** (there is usually a maximum of 20 epochs available).

**Common criteria that can be utilized for future model**: Before creating my long term model to predict a "complexity" score, I will define what factors may contribute to the complexity/ difficulty of an origami model.

- Number of folds (fold count)
- Complexity of folds (e.g., valley folds vs. mountain folds)
- Size of the paper used (larger paper tends to provide more fold space for complex models; thinner paper is also more ideal for folding)
- Original paper dimensions to origami dimension ratio (smaller models with a high fold count may prove to be more complex than their larger counterparts)
- Techniques required (e.g., reverse folds, sink folds)
- Time taken to fold the model (fold times)
- Aesthetic score (provided by AI)
- Commonality of model (popularity of origami structure)
- Adjusted difficulty score (based on fold count and fold time)

## CHALLENGES AND CONCLUSIONS

When conducting this study, one of the challenges I encountered was the difficulty in finding data on the number of folds for each origami structure. As I also had to figure out the distinction between a fold and a movement, I think going forward I will consider any crease (contributing to the final model) a fold and scale up my future model to account for this while it predicts a complexity score.

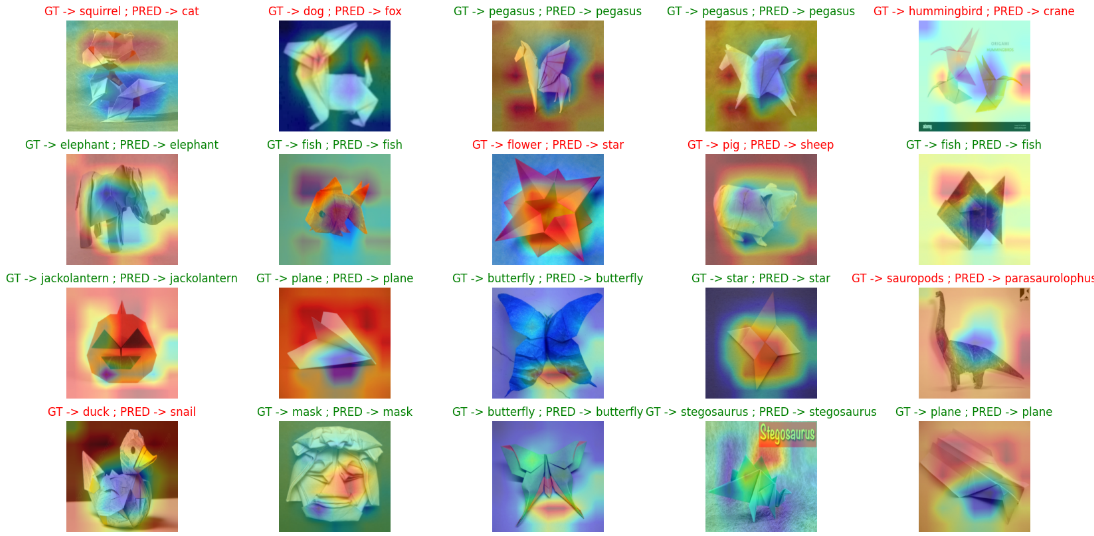


**Figure 9.** Classified origami names based on png images from a 3000 count dataset (produced an accuracy of 0.71)

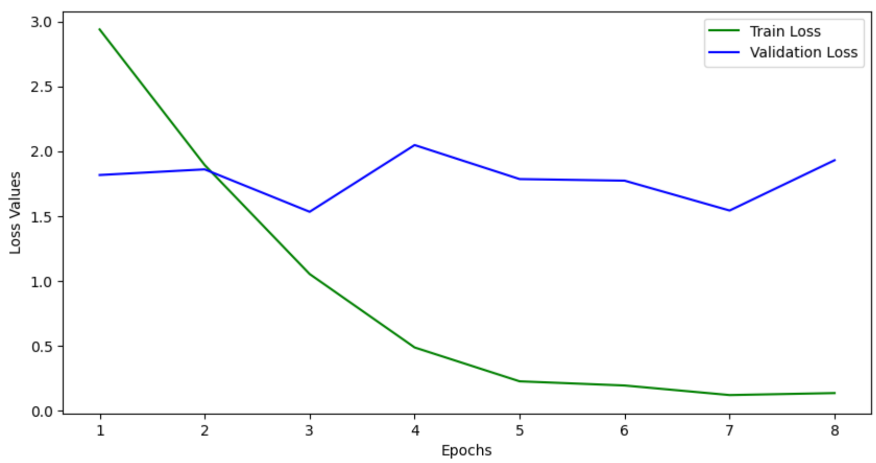


**Figure 10.** Validation loss and training loss over multiple epochs (Model improves quickly then stabilizes after loss value does not decrease for 5 consecutive epochs)

**This project appears to align more closely with Artificial Intelligence (AI) techniques than with traditional Machine Learning (ML) methodologies**, but there were other challenges that involved scraping the origami website page. This was due to the fact that, as the first page was a generic link ”https://origami-database.com/models/”, pages 2-37 followed the form ”https://origami-database.com/models/page/, which made it easier to scrape information from those pages but harder to scrape models from the original first page.

Other challenges included the discrete nature of the difficulty criteria in the main dataset as no continuous variables were used (only in the case where I averaged the difficulty of models with the same time, which gave me an R-squared of 0.582).

## Future Involvement

Based on the decision trees and gradient boosting methods, in the future I will look to hyper-tune parameters and use AI to provide a complexity score that determines how many Orgs (points) an origami structure is worth. I will also advance my image recognition neural network to accurately predict a greater number of photographed origami models.

Eventually, I will create a website where users will be able to paste a picture of an origami model before its value is predicted and replicated in a digital database. To create newer more diverse digital origami, I will use JS (JavaScript) code from Amanda Ghassaei's free to use github (https://github.com/amandaghassaei/OrigamiSimulator) to generalize and animate new models (for potentially 3 more structures). From there, I will show off the updated web application in D3.js. (Note: I have provided an animated python plotly regression chart documenting origami images, descriptions, and names)(In github and on Youtube).

## 3 RESOURCES


1. https://origami-2.database.com/models/ - Origami Database
2. https://en.origami-club.com/index.html - Provides Origami diagrams
3. https://www.kaggle.com/datasets/karthikssalian/origami-models - Origami classification dataset
4. http://www.origami-instructions.com/ - Origami model creation instructions
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