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Introduction

Neural Networks play a pivotal role in machine learning. They are highly adaptable and capable of accommodating diverse data types. Their ability to handle large datasets and complex problems positions them as essential tools for addressing contemporary data analysis challenges in fields like healthcare, finance, and marketing.

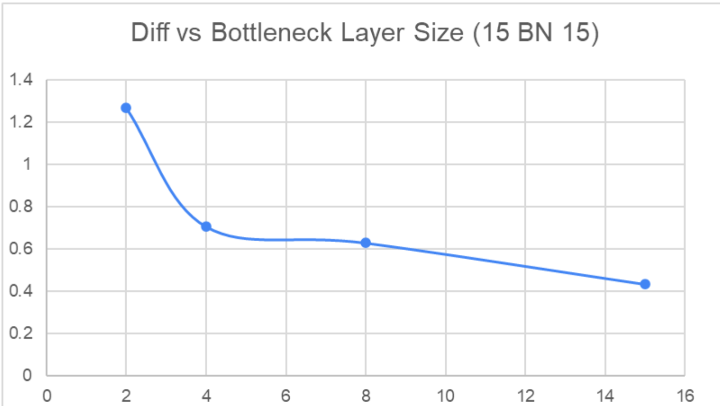
A neural network consists of nodes sequenced into an input layer, hidden layers, and an output layer. Each layer consists of nodes that establish connections with one another, characterized by specific weights and thresholds. When the output of an individual node surpasses a predefined threshold, it becomes activated, forwarding data to the subsequent layer in the network. Although initially training neural networks is time consuming, extensive amounts of training can improve its ability to analyze data. This allows us to perform large amounts of repetitive tasks quickly and efficiently.

Autoencoders are a type of neural network that is implemented in unsupervised learning. An autoencoder consists of an encoder, a latent space, and a decoder. The encoder takes the input data and compresses it into a lower dimensional representation. This representation is often referred to as the latent space or the bottleneck. The latent space captures the most essential features of input data provided by the encoder and disregards the less important features and sends them to the decoder. The decoder takes the reduced representation of the input data and expands it back to the size of the original representation. The primary goal of autoencoders is to minimize the difference between the input data and the data generated by the encoder and decoder. Achieving this allows it to capture significant patterns and features in a dataset.

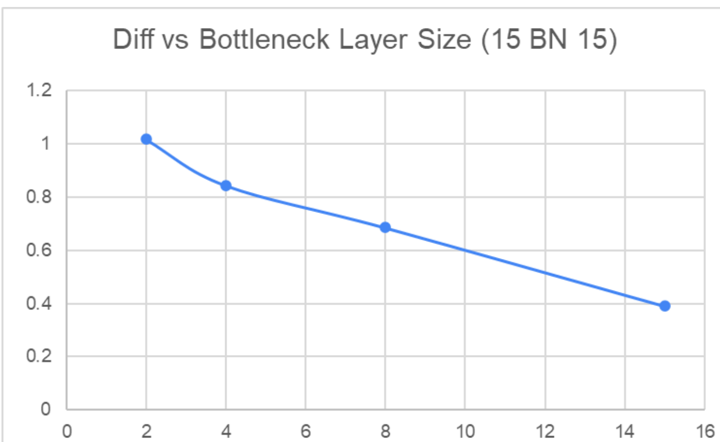
Methods

In my research, I was tasked with optimizing the performance and reliability of materials utilized in aircraft engines based on 15 distinct characteristics. My goal was to optimize features of the materials utilizing my knowledge of autoencoders to reduce the mean and standard deviation of each characteristic from 15 dimensions each to 2 dimensions each. By reducing the feature space, I was able to analyze and manipulate the critical properties of engine materials efficiently. In order to achieve this I measured the average difference which is the average loss that the data encounters during each test. I calculated this value by normalizing the difference between the test values and the decoded data and averaged out each diff across each test. For each test, I calculated the diff for every bottleneck size from 2 to 15 for each batch size from 4 to 64. I also performed this set of tests on both a single pair of encoders and decoders and 2 pairs of encoders and decoders. For the sets of 2 pairs, I repeated the experiment on varying node sizes from 2 to 15.

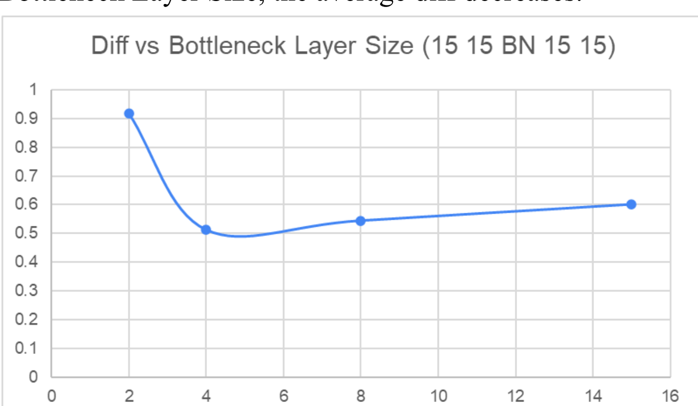
Results



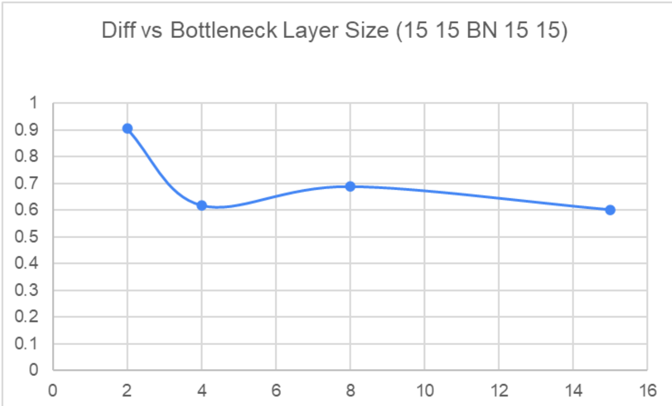
This is the graph for the Mean Diff for an Autoencoder with 1 input layer with 15 nodes, 1 Bottleneck Layer, and 1 output layer with 15 nodes. This graph shows that as you increase the Bottleneck Layer Size, the average diff decreases.



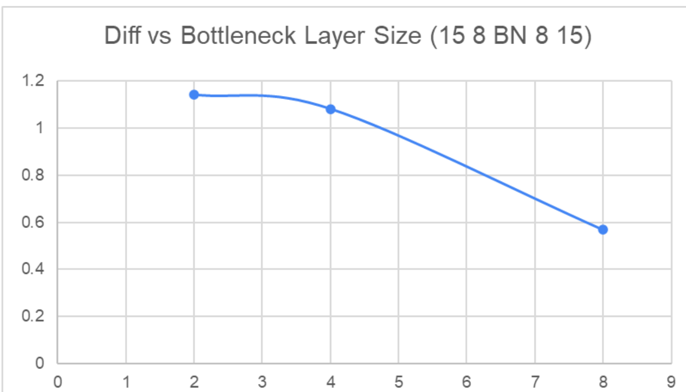
This is the graph for the Standard Deviation of the Diff for an Autoencoder with 1 input layer with 15 nodes, 1 Bottleneck Layer, and 1 output layer with 15 nodes. This graph shows that as you increase the Bottleneck Layer Size, the average diff decreases.



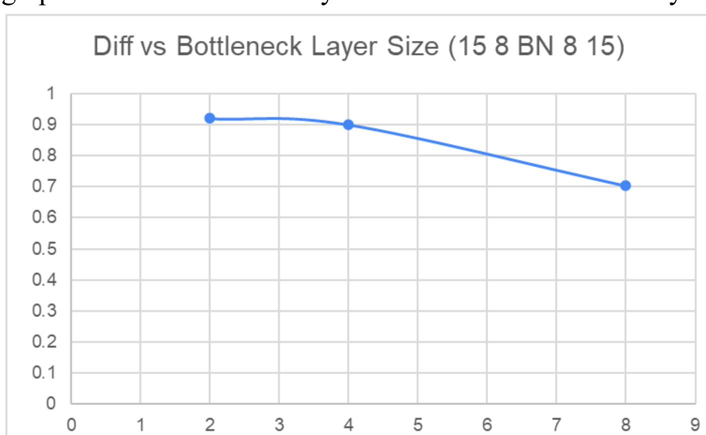
This is the graph for the mean Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 15 nodes, 1 Bottleneck Layer, 1 decoded layer with 15 nodes, and 1 output layer with 15 nodes. The graph shows that it levels out as you increase the bottleneck layer size and its lowest is at 4 nodes.



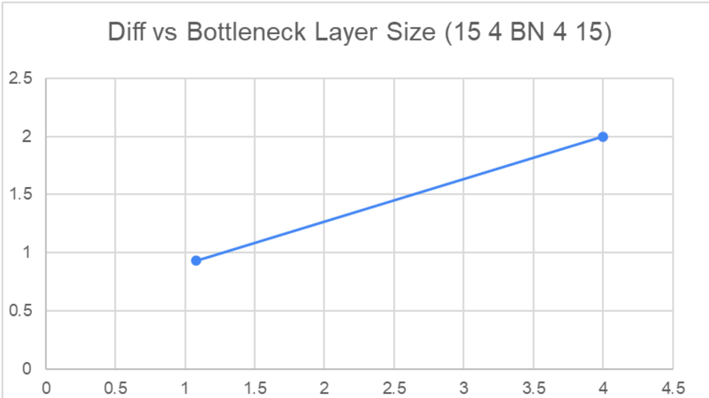
This is the graph for the Standard Deviation of the Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 15 nodes, 1 Bottleneck Layer, 1 decoded layer with 15 nodes, and 1 output layer with 15 nodes. The graph shows that it levels out as you increase the bottleneck layer size and its lowest is at 4 nodes and 15 nodes.



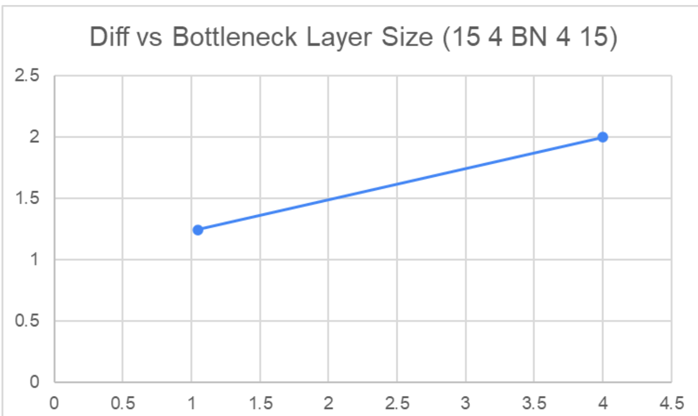
This is the graph for the Mean Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 8 nodes, 1 Bottleneck Layer, 1 decoded layer with 8 nodes, and 1 output layer with 15 nodes. This graph demonstrates that as you increase the bottleneck layer size, the average diff decreases.



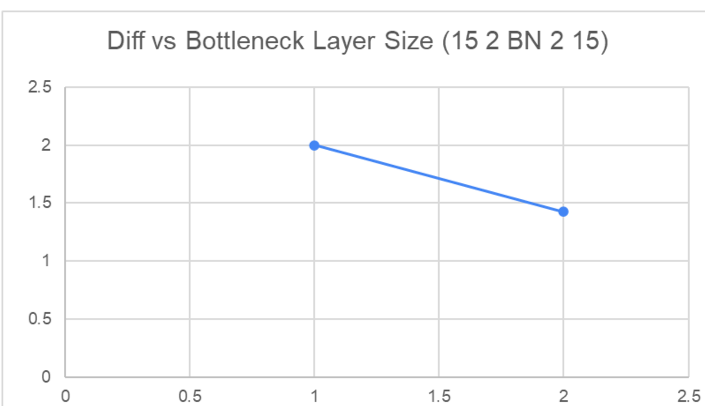
This is the graph for the Standard Deviation of the Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 8 nodes, 1 Bottleneck Layer, 1 decoded layer with 8 nodes, and 1 output layer with 15 nodes. This graph demonstrates that as you increase the bottleneck layer size, the average diff decreases.



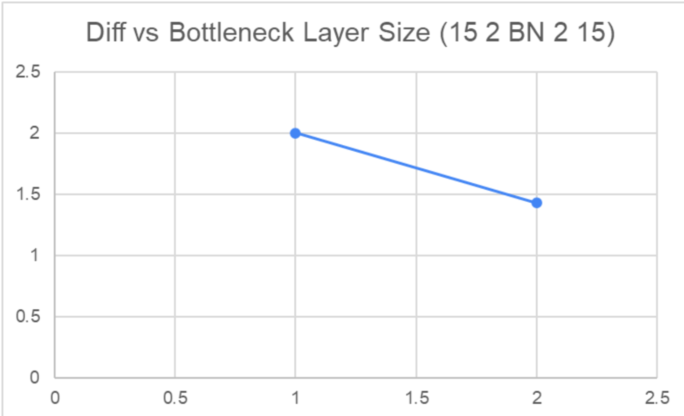
This is the graph for the Mean Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 4 nodes, 1 Bottleneck Layer, 1 decoded layer with 4 nodes, and 1 output layer with 15 nodes. This graph demonstrates that as you increase the bottleneck layer size, the average diff increases.



This is the graph for the Standard Deviation of the Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 4 nodes, 1 Bottleneck Layer, 1 decoded layer with 4 nodes, and 1 output layer with 15 nodes. This graph demonstrates that as you increase the bottleneck layer size, the average diff increases.



This is the graph for the Standard Deviation of the Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 2 nodes, 1 Bottleneck Layer, 1 decoded layer with 2 nodes, and 1 output layer with 15 nodes. This graph demonstrates that as you increase the bottleneck layer size, the average diff decreases.



This is the graph for the Standard Deviation of the Diff for an Autoencoder with 1 input layer with 15 nodes, 1 encoded layer with 2 nodes, 1 Bottleneck Layer, 1 decoded layer with 2 nodes, and 1 output layer with 15 nodes. This graph demonstrates that as you increase the bottleneck layer size, the average diff decreases.

Next Steps

To advance my research, I intend to explore numerous strategies regarding reducing the average difference, including introducing a range of encoded and decoded layers with varying node sizes into the autoencoder. This approach is motivated by the recognition that the depth and complexity of the neural network plays a pivotal role in determining its ability to capture meaningful data representations and minimize reconstruction errors. Through a systematic experimentation process involving different layer configurations, I aim to discover the deeper connection between depth and model performance as well as develop an accurate method for optimizing the performance and reliability of materials utilized in aircraft engines.