# Stenotic Nares Report – technical version

Disclaimer: all accuracy figures below are based on only 100 validation images, so take it with a pinch of salt.

Aim: create a deep neural network (a form of Machine Learning) algorithm that can distinguish between dog with and without stenotic nares

## Result:

Achieved overall accuracy of 83%, and in particular predicts images with stenotic nares with 94% accuracy.

## Key challenge:

Lack of data (I handpicked 400 images from google here) which is by far the biggest limiting factor to model’s performance. This has led to a number of compromises below.

1. Due to small dataset, I’ve categorised all degrees of severity of stenotic nares under stenotic nares category, even though they may carry drastically different risk level.
2. I’ve used a separate model to recognise dog’s key facial features in order to crop the images of dog down to just the nose region. Model is not perfect. Sometimes model gets the features wrong by a long way, cropping is slow and certain images seem to make the model get stuck (rare occasion and I can’t find a reason as to why this might happen, or any pattern as to what sort of image causes this). However the algorithm does fine for small scale applications such as cropping a few images at a time for prediction.
3. For testing new images, ideally we want a frontal image of dog with face (and nose) clearly visible. The facial feature recognition model will do much better if the face is reasonably up right.
4. Due to exceptionally small dataset and auto cropping process removed a lot of the learnable features, deeper (or more complex) neural networks and transfer learning performs poorly in this case.
5. I’ve created 3 independent models, each with accuracy around 80-81%. Then I combined the predictions from all 3 to reach a final prediction on an image, with overall accuracy of 83%. The performance increase is marginal in this case, but in theory we can hope to see a much bigger improvement from this approach if we go full scale and work with a large dataset.
6. Since improving the overall performance of the model is difficult, I’ve introduced some conscious bias in the model so that it can predict images WITH stenotic nares with 94% accuracy. The thinking behind this is that if we think a dog with stenotic nares as health and write the policy, then we might make a loss in future when the dog needs an operation. But if it was the reverse, then we just don’t make a gain or a loss.
7. Models very confident in its predictions even when it’s wrong. Likely a case of over fitting due to small dataset.

## How we can improve this model further:

1. MORE DATA. 400 images are simply inadequate for training a deep neural network. It would help alleviate a lot of the problems above, and perhaps even remove the need for a separate network to performing auto cropping.
2. Better application of transfer learning technique. Here I used a very basic application of transfer learning: that is taking an existing network then simply retrained its final layer. With a dataset so specific and simple, I believe we will obtain much better result by only taking the very first few layers and weights, and then retrain the subsequent layers.

## Conclusion:

I believe we can indeed develop powerful deep-learning applications internally, given the right data and some support from the rest of the business. I hope through this project I’ve highlighted the value in collecting / retaining data such as images of the pet insured.