**Week 1:**

We were assigned the catheter group project, and the week was dedicated to understanding the project’s goals and background by reading through the Kaggle post, looking through the dataset we were given. Our group coordinated a general idea of what we wanted to each do, however at this point we all lacked a firm understanding of neural networks and how to approach the task. I did a little bit of research into catheters and neural networks however I struggled to understand how they worked as it was a completely new and seem very daunting and complicated.

**Week 2:**

Further research was done the project, and we began the EDA process. We found that the data did not need processing as there was not any need for reformatting or replacing any values as the dataset was simply just an ID, what catheter position and its corresponding image ID. We began talks of how we would like to approach the project and discussed how we would image the neural network to function. We would have liked the model to be able to detect the type of catheter and then be able to correctly classify the position, however at this point we were unsure how to implement this.

**Week 3:**

This week we solely discussed on how we were going to get the neural network to take images as inputs. After some research and talking with our TA’s, we knew they had to be converted to NumPy arrays so that the image is read as a matrix. We researched into how this was accomplished but I had some trouble as my main source of knowledge was following guides on how to create neural networks, however all the examples I saw used preformatted data sets that had the images already converted to arrays, so there was no practical step by step guide on how to accomplish that.

**Week 4 and 5:**

These weeks have been merged as these weeks were dedicated to converting the images to arrays. We had many issues accomplishing this as we ran into many errors that we did not understand. Even following the steps of the other group, we could not get our arrays to work. At this point the overall group progression halted and only really me, Colin and Huda were working towards solving this problem. I did more research into the type of neural network we could build. I found many sources including the Tensorflow website on how image classification works, and I also investigated image segmentation would look more appealing as it could identify multiple parts of an image. For example, it might have been able to detect the person’s collarbone which would give the model an idea of where the catheter should be with respect the position of the collarbone. This would be an ideal solution as I realised looking through the images, everyone’s body is vastly different in size and proportions. Meaning a catheter may be in the correct position for one person but may not be for another. Although we should have assigned everyone to try overcoming this hurdle, the other team members did not seem to attempt to help.

**Week 6:**

From the first 6 weeks I realised how difficult real world data sets can be. Up and until now, our datasets have been relatively easy to process, however this is my first-time encountering image data, and I did not realise the challenges ahead of me. At this point, our problem with the arrays had not been resolved and as such I sought to find an alternate solution. I had found a guide to neural networks that had unprocessed images and implemented a method that auto converts the images to arrays. Following that, I did a very simple neural network with Resnet50, that only used a couple of images in the validation and testing set as GoogleColab had issues with ram usage. The model was working and was a proof of concept and an alternative solution if we could not convert the images ourselves. What I quickly realised from working on this project was task delegation, more specifically being vocal and directly telling team members to help as it was the same people working on the code and the others not doing much; on occasion joining discussions. As this is a new experience for all of us, having multiple people try their own methods to convert the images to arrays, would help speed up the process, instead of us banging our heads against the wall.

**Week 7:**

This week I tried to implement more images to my model however I quickly realised the limitations to it. Firstly, I had to manually download the images onto my computer and save the different catheter positions into subfolders and then run it through my model. If I were to follow this path, I would need to manually sort through the dataset and find the corresponding image to the catheter position and individually download them. After talking with Simon and Zach, they suggested I create a for loop function that could iterate through the dataset and then download them into their corresponding subfolder. After discussions with the group, we decided this may not be the best idea for a couple of reasons. Firstly, the computation power needed could not be provided by GoogleColab as we and yet to gain access to Massive. Secondly, since the images were being processed and converted in real time, if we were to implement hundreds or thousands of images, it would take too long as running the model with just 2 images in each position with 5 epochs took almost 10 minutes.

**Week 8:**

We had successfully converted the images to arrays, and we could commence building our models. From looking at the Kaggle submissions, we saw that many groups were using some derivative of Resnet. So, I focused my attention on just Resnet and attempted DenseNet however discontinued that as I was struggling to get that to work. We decided to focus on just CVC catheters as it was simpler and we were unsure how the model would deal classifying different catheters, let alone its position. I played around with the different hyperparameters such as batch size, epoch, image dimensions, learning rate and more to see how the model would react in terms of the accuracy. I also played around different number of layers and the number of neurons. My goal was to see if there was an intuitive pattern with changing all the parameters however there was no obvious relationship that I could see. Huda and I discussed the possible approaches we could take and the biggest suggestion I had was the dimension size as intuitively, decreasing the dimensions from its native (2000x2000 roughly) to 224x224 would reduce the computation power needed at the cost of information as there is less pixels to observe. Besides that, we decided to incorporate the annotated dataset so that our model could learn from those first. In terms of group progression, we had Colin to setup and begin the report and Huda and had the skeleton format for the presentation done.

**Week 9:**

At this point I took a step back from the code for modelling as I had trouble running Massive, it required many pips to be installed and updated which Colin and Huda spent 2 hours in a previous class doing, however they did not remember what they specifically installed. So, my job now was to help and give suggestions to Huda on how to improve the models. We had converted the annotated data set into arrays, so we began running our models through those with improved scores compared to just training the model on the training set. We attempted to train the model twice, first with the annotated dataset and then the normal training set. However, what we discovered was that we got worst scores which contradicts what we thought would happen as we thought, the weights would be fairly accurate from the annotated dataset.

**Week 10 and 11:**

At this point we decided to introduce new aspects to the model as we were running low on time. We were introduced in class about SMOTE and other oversampling/undersampling techniques however we did not try these in time. We mainly focused on tweaking the parameters to try and achieve better accuracies. At this point we finalised our models and were set on completing the slides for our presentation and began writing the report. We asked what everyone wanted to do for the presentation and what to write on the report. I had written my part of the presentation and did the respective slides. However, we ran into some issues with the other groups members presentation sections. At this point the other 2 group members had not really been keeping up with the groups progress and generally lacked the understanding on the project itself and what we had accomplished which was obvious in their sections of the report and presentation. We edited their sections of the report so that it was correct and aligns with the groups goals and corrected any mistakes in their part of the presentation. Although, it is their responsibility to keep up with the groups progression, which they did not attempt to, I could of still taken the initiative in updating and going through with them what we had done so that they are on the same page.

**Week 12:**

Working on this project has been very enjoyable for me, not only was it related to the health sector that I am familiar and interested in, I also go to experience the challenges of creating complex neural networks. However, looking back I had a lot to improve on. Firstly, I should not have just ignored the other group members and leaving them in the dark, even though it was unintentional. Instead of being annoyed that they aren’t putting any effort in or helping the group in any constructive way, I should have at least talked to them and explained what we had done so that they could complete the tasks for the presentation and report correctly. Although I know the importance of working as a cohesive group is important, it was more prominent as ever within this project as the workload was far beyond other projects. The biggest change I would make if I encountered another project such as this, is to firmly solidify my knowledge on the type of model we are using. Although I did some preliminary research on neural networks, I did have a firm grasp on how they worked and how specifically Resnet50 functioned until around week 11 for the report. The biggest hurdle when researching neural networks and Resnet50 was that majority of the resources explaining the process was quite complicated and was generally just daunting, so I steered away from properly understanding them. What I should have done earlier was use CHATGPT to explain those concepts as I find that CHATGPT is a useful resource in explaining concepts. Bouncing back and forth and other resources and CHATGPT, I understand how Resnet50 functioned and would explain why our model was not as good as it could have been. Firstly, I had discovered that Resnet50 was mostly trained on Imagenet, which only contained images of size 224x224 such that the architecture for Resnet50 was in purpose for those dimensions, which would explain why my models never improved from increased dimensions. Furthermore, the Imagenet database did not have any images on x-rays or catheters so it had no pretraining for our models, so it would have possibly been more practical to start with None weights. To combat the 224x224 architecture, it would have been better to keep the images close to their native size and construct our own layers such that the last layer or fully connected layer would match the feature map of a large input size. Although, implementing these changes may have been difficult and beyond our capabilities, having this detailed knowledge earlier would have greatly sped up the trial-and-error purpose and could have left us with more time to experiment with our model. Furthermore, I realised too late that our annotated images may have introduced a new variable to our model, which was the catheter placement was highlighted in blue circles, which means the model was learning that blue dotted circles mean the features are there. However, when we go on to test our model, none of the images would have blue or circles. So, in essence, we had introduced 2 new variables, circles and the colour blue which is especially bad as the images were only black and white. However, from this project, I have gained a strong foundational knowledge of neural networks and Resnet50 and understand the challenges of building neural networks and can apply my new attained knowledge to future endeavours.