PREDICTING SPATIAL DISPLACEMENT BASED ON INTRAOCULAR IMAGE DESIGN USING CONVOLUTION NEURAL NETWORK – PRELIMINARY FINDINGS

MOHD IZZUDDIN MOHD TAMRIN[1*], MOHD ZULFAEZAL CHE AZEMIN[2], NOOR FAWAZI MD NOOR RUDIN[3], MOHD HAZIMIN MOHD SALLEH[4], MOHD RADZI HILMI[2], ALI AMER ALWAN[1], ASADULLAH SHAH[1]

[1]Kulliyyah of ICT, International Islamic University Malaysia, Gombak, Malaysia
[2]Kulliyyah of Allied Health, International Islamic University Malaysia, Kuantan, Malaysia
[3]Malaysia-Japan International Institute of Technology, Kuala Lumpur, Malaysia
[4]Kulliyyah of Science, International Islamic University Malaysia, Kuantan, Malaysia

**Corresponding author: izzuddin@iium.edu.my*

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ABSTRACT: The main global cause for blindness is due to cataract. The common treatment for cataract is to have the cloudy natural lens removed and replaced with an artificial intraocular lens (IOL). Success in the post cataract surgery depends on the design and quality of the IOL implanted on the eye. ISO11979-3 is the standard adhered to by many lens manufacturers, to test the mechanical stability of the lenses that they produced. This compression test experiments on the lab are very costly and time consuming. Alternatively, we propose to use the convolution neural network (CNN) to predict the spatial displacement response based on the intraocular image designs. Due to limited number of images in the datasets, data augmentation was performed to transform these images and increase the sample size to 240. On top of this, the ResNet-50 deep learning network architecture was utilized to transfer the learning done on over millions of images. The final RMSE value for the training set, validation set and testing set were at 0.47mm, 2.93mm and 2.92mm respectively. The model predictabillity is well within the range recommended by the standard between 0.15 to 1.98 mm.

KEY WORDS: *Intraocular Lens (IOL), Spatial Displacement, Convolution Neural Network (CNN).*

1. INTRODUCTION

In Malaysia, 39% of the cases for bilateral blindness are due to cataract according to the Malaysian National Eye Survey (Chew, Salowi & Mustari et. al., 2018). According to the World Health Organization, 51% of the main global cause for blindness is due to cataract (Pratap & Kokil, 2019). The common treatment for cataract is to have the cloudy natural lens removed and replaced with an artificial intraocular lens (IOL). The success in the post cataract surgery also depends on the design and quality of this IOL implanted in the eye. The ISO11979-3 standard is adhered to by many lens manufacturers, to test the mechanical stability of the lenses they produced (Lane, Collins, Das et. al., 2019). There will be high costs incurred to the manufacturer, to measure the spatial displacement, when conducting these test compression experiments in the lab.

These measurements include optic decentralization, axial displacement, optical tilt, and compression force. The compression test for these lenses must lie between the range of 0.005 to 0.28 mm, 0.15 to 1.98 mm, 0.07 to 1.07 degrees, and 0.25 and 4.14 mN respectively (Remón, Siedlecki & Cabeza-Gil et. al., 2018). In contrast, finite element analysis (FEA) is one of the most employed methods to simulate real-world problems using mathematical and engineering models. Figure 1 illustrates the layout of this compression test that is required by ISO11979-3 standard. Utilizing the FEA to simulate these tests will eventually reduce the costs for testing and shorten the time to choose the best new design for the IOL. However, the identification of the material used to create the IOL is vital, prior to carrying out the simulation. The Fourier-transform infrared spectroscopy is one of the most reliable and accurate methods to extract materials properties from any sample.

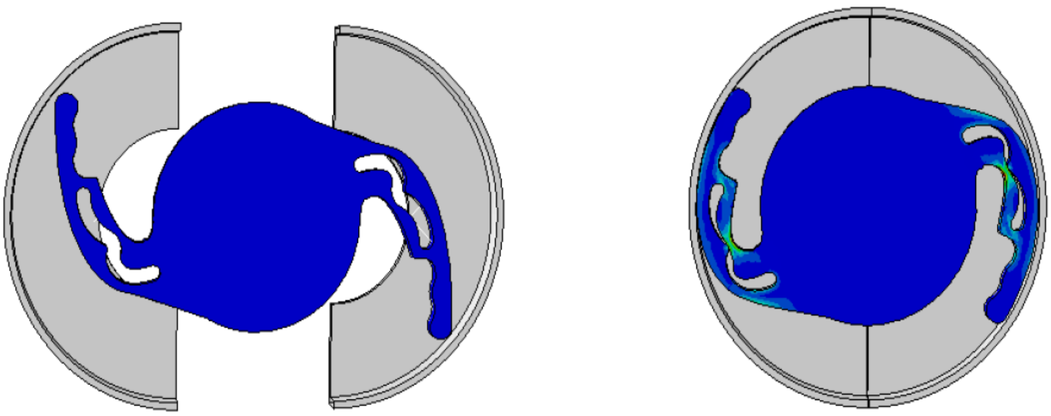

Fig. 1. Compression Test Layout based on ISO11979-3 Standard.

Once the materials' properties are identified, the mechanical characteristics can easily be determined such as the density (Karthick, Sirisha & Sankar, 2014), elasticity (Okeke, Thite & Durodola et. al., 2017) and friction co-efficient (Nuño, Groppetti & Senin, 2006), and configured for the simulation. While simulation with FEA offers cheaper and more flexible alternative to the physical test, the time taken to process a model can vary between hours and weeks depending on the complexity of the simulation (Hume, Rullkoetter, & Shelburne, 2020). This can hinder the ability to quickly estimate the impact of a new design on the optical displacement of these intraocular lenses. Our research project aims to automate the prediction of the mechanical stability for any new IOL design by using the convolution neural network (Cabeza-Gil, Ríus-Ruiz & Calvo, 2020; Fernández-Álvarez, Hernández-López & Cruz-Cobas et. al., 2019). The convolution layer can break these images into local patterns, and as it progressively moves towards one layer after the other, it will learn a more complex and global concepts (Imran, Li, and Pei et. al, 2020a).

Moreover, the position of these local patterns on the intraocular image design are not of importance, as they can either be on any location that is either on the right top corner or right bottom corner. Therefore, there will be no calibrations needed, prior to feeding these images into the convolution neural network.

However, having small test cases from the simulation can cause data overfitting and the inability for this neural network to generalize to new data. This can be addressed with the introduction of data augmentation layer. It generates more training data by making small changes to the existing images, so that the neural network is exposed to different aspects of these images for better generalization (Imran, Li, and Pei et. al., 2020b). Lastly, existing deep learning network architecture, the ResNet-50 can be employed and customized to suit our prediction system. This can ultimately increase the sensitivity of our intelligence system.

2. METHODS

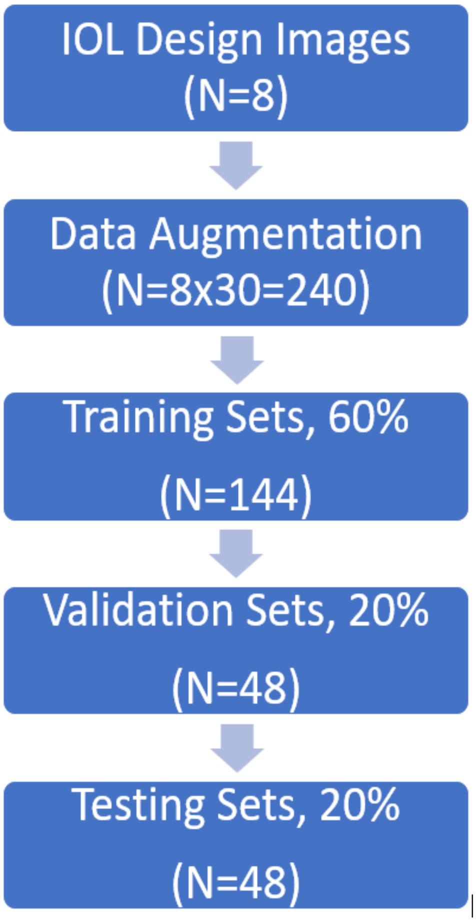

Fig. 2. Flowchart of Intraocular Image Design used for the Training, Validation and Testing sets.

In this section, the entire process involved in training the convolution neural network for the prediction of spatial displacement will be deliberated extensively. Firstly, as summarized in figure 2, it is important to establish the source of the datasets that will be used in this study. In our previous project, eight intraocular lenses were simulated to undergo the standard ISO11979-3 compression test using finite element analysis (FEA). From these simulations, the compression force, axial displacement, decentralization, and tilt were measured for each lens. These intraocular image designs will be used for the training, validation, and testing sets in the development of the convolution neural network. Since we are still in the early stage of this study, only the axial displacement was selected as the predictor for the spatial displacement. The reason for this is that if the measurement lies outside of 0.15 to 1.98 mm, it can cause blurriness to the vision after surgery.

Fig. 3. Transformation of the Introcular Image Design using Data Augmentation.

However, we still have a small dataset to work with. Using only this limited data to train our convolution neural network can cause overfitting to the prediction model whereby it will not able to generalize to a new set of data that it has not seen before this. Data augmentation (Shorten & Khoshgoftaar, 2019) is a technique that can be employed to mitigate this problem and increase the size of datasets. The image design will be transformed by randomly rotating, shifting to the left and right, flipping horizontally and vertically, and performing shear mapping to these images. Figure 3 demonstrates the results of these transformations for one of the eight intraocular lens. With these transformations, we have generated 30 additional images for each one of these eight image designs. Ultimately, we have a total of 240 images. Next, 60%, 20% and another 20% of these images were split into the training sets (N=144), validation sets (N=48) and testing sets (N=48) respectively.

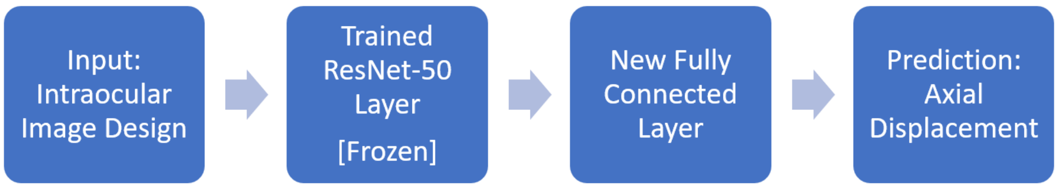

Fig. 4. Customized Layers of the ResNet-50 Deep Learning Network Architecture.

Utilizing a pre-trained network such as ResNet-50 (Imran, Li & Pei et. al., 2020) can be advantageous because it has been trained over millions of images. Considering that we have small numbers of datasets, the accuracy of our prediction can increase even further with ResNet-50. This network architecture comprises 50 layers deep, and mostly made up of skip connections and batch normalization, to reduce the problem with vanishing gradients during the process of backpropagation. However, we need to customize it by adding a new fully connected layers on top of its head, to suit our application. In that, we can take in the intraocular image design, to predict the axial displacement response. Figure 4 summarizes our customized layers of the deep learning network architecture. To speed up the process of training this network architecture, we can freeze all 50 layers of ResNet-50 that we assumed to have been optimized from previous learning and update only the new fully connected layers.

Table 1: Hyperparameter Set for Network Training

Property	Value
Batch Size	10
Learning Rate	0.0001
Epoch	30
Validation Steps	Every Epoch

Table 1 summarizes the configuration of the hyperparameter used for training this customized deep learning network architecture. To determine the performance of this network architecture in making a good prediction, a loss function, mean squared error and root mean squared error were introduced. The former calculates the average squared of error between actual and predicted values whereas the later calculates like a normalized distance of error between actual and predicted values. The definitions are as follow:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2} \tag{2}$$

Where n is the number of intraocular image designs that are fed into the network architecture, y is the actual value for the axial displacement whereas ŷ is the predicted value.

3. RESULTS AND DISCUSSION

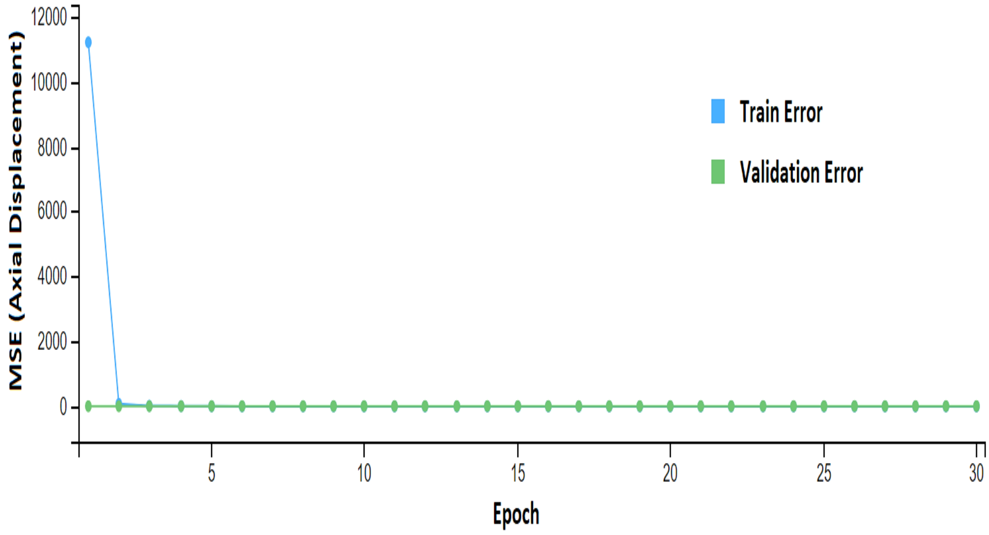

Fig. 5. Learning Curve for the Deep Learning Network Architecture. Representing Mean Squared Error for Axial Displacement as Function of Epoch of Training.

In this section, we highlight the results of the trained deep learning network architecture followed by a brief discussion. Figure 5 illustrates the learning curve for the network architecture to predict the axial displacement response from merely the intraocular image designs. It represents a loss function, the mean squared error for axial displacement response as a function of number of epochs of training. Not as what we were expecting, immediately after the second epoch, the training error dropped drastically from 11208.73mm to 78.27mm. After that, the error gradually reduced in smaller amount until it reached to 0.22mm at the end of 30 epochs. On the other hand, the level of validation error was slightly higher than the training error. This is as expected because this model had not yet seen the data in the validation sets. It started from 5.98mm and stalled around 8.59mm at the end of 30 epochs.

Table 2: The Final Prediction Error at 30 Epochs for Training, Validation and Testing Sets.

Sets	**Axial Displacement (mm) [MSE]**	**Axial Displacement (mm) [RMSE]**
Training	0.22	0.47
Validation	8.59	2.93
Testing	8.50	2.92

Table 2 shows the final prediction of the axial displacement response, after 30 epochs for training, validation, and testing sets with the MSE values of 0.22mm, 8.59mm and 8.59mm, respectively. On the other hand, the RMSE value for these sets are 0.47mm, 2.93mm and 2.92mm, respectively. Figure 6 demonstrates our model predictability, for the axial displacement response. 48 of the intraocular image designs from the testing sets were used to evaluate the performance of our model against the actual values. The red diagonal line in the graph shows the ground truth. As we can see, the prediction made by our model is still within the range that were proposed by the standard which is between 0.15 to 1.98 mm. Since we are still in the early stage of our project work, there are still room for improvement to minimize the differences in the error values in the future. We can increase the ability for our model to make better prediction, by increasing more variability between the samples in our datasets.

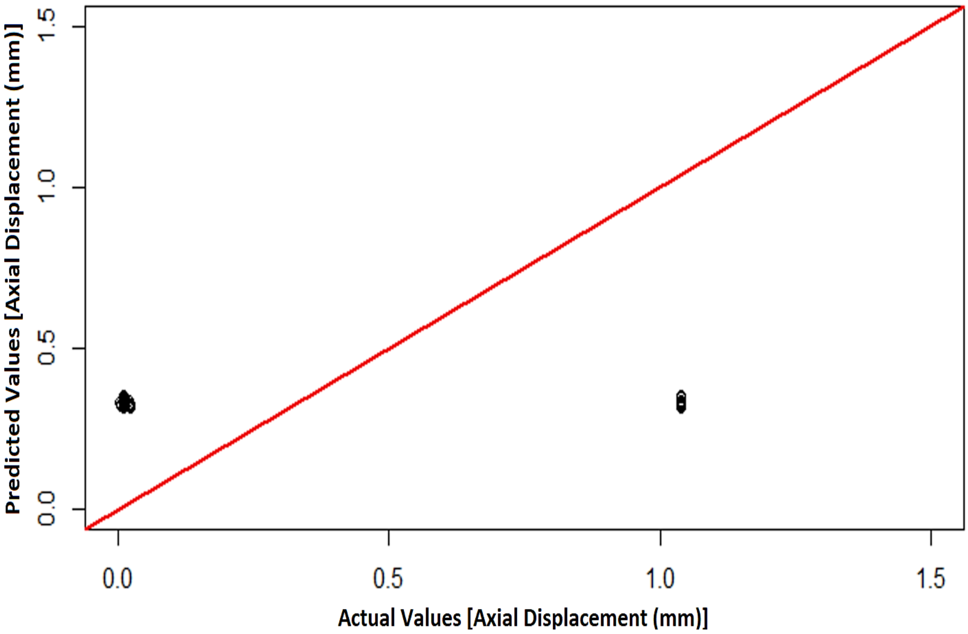

Fig. 6. Model Predictability for the Deep Learning Network Architecture: 48 Predicted Values for Axial Displacement are Compared with the Actual Values

4. CONCLUSION

Looking back at the predictability of our model that were discussed at length in the previous section, this can be an indicator that we are on the right track. As we have mentioned before this, the prediction made by our model is still within the range proposed by the ISO11979-3 standard, which is between 0.15 to 1.98 mm. Moving forward, we still need to fine-tune our deep learning network architecture. With the limited number of intraocular image designs in datasets, we have employed data augmentation technique to transform our initial images to increase our sample size to 240. Moreover, we have utilized ResNet-50 to transfer the learning over millions of images to optimize the weightage of our new fully connected layers. In the next phase of our project work, we are considering to better improve the predictability of our model by introducing more variability between our samples.

To do that, we need to carefully plan and generate more simulations for the standard compression test via the finite element analysis (FEA), on all kinds of intraocular image designs. This can take up a lot of the computational time. However, once these intraocular image designs have been trained by the convolution neural network, it can immediately within split microseconds, finds the spatial displacement response regardless of which intraocular lens design that is fed into our deep learning network architecture. The applicability of our model has significant impact for the health care practitioners and the intraocular lens manufacturers. In that, our model can reduce the time and costs for unnecessary testing, by automating the prediction of the mechanical stability for any new IOL designs.

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