# Deep Learning for Glistening Quantification in Intraocular Lens

Kay Thwe Min Han, Bunyarit Uyyanonvara, Kotani Kazunori, Chris Hull

***Abstract*—Glistening Quantification is essential to assess the quality of the lens and to assign appropriate treatment after the cataract surgery. Glistening increase forward light scattering and affect human vision. Glistenings are observed and graded in intraocular lens by clinicians through slit-lamp. Several studies report to grading by number of glistenings present in Intraocular lens (IOL). Since glistenings are small water inclusions in IOL and can be observed with different sizes. Manual Clinical grading is time consuming to finish each IOL and moreover, inaccurate. Therefore, one of the methods to quantify glistenings in IOL is required for both clinicians and patients. In this paper, Deep Learning approach based on convolution neural network is trained to quantify glistening in IOL. The result shows the proposed method can automatically classify glistenings in vitro IOL image and predict the probabilities of glistening in IOL.**

***Index Terms*— glistening detection, quantification, classification, deep learning**

## I. INTRODUCTION

GLISTENING are fluid-filled microvacuoles in Intraocular lens which can be observed after cataract surgery. [1] [2]The lens is made up of water and protein molecules. In fact, the cataract is associated with aging process because the proteins of the lens start to clump together and cloud the lens is called a cataract. [3] [4] [5] [6] [7] However, this cloudy lens affect vision and therefore, Intraocular lens, medical devices that are implanted inside the eye and removed the natural lens during cataract surgery. [8] Glistenings are observed after 2 or 3 years of implanted surgery and occurred 90% in AcrySof® lenses. [9]

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The formation of glistenings is observed in the temperature changes of the lens from room temperature to body temperature in which the material absorbed water allowing to collect into voids within IOL over an extended period and form fluid-filled bubbles. [10] These bubbles appear to sparkle under slit-lamp examination and glistenings can affect the light scatter in IOL. Therefore, glistening grading is assessed by clinicians observing in vitro through a slit-lamp. [11] Yet, clinical grading is time consuming and the manual grading results are challenging due to distribution, number and size of glistening in IOL.

Glistening detection with image processing techniques has been observed from the previous studies. The algorithm based on blob detection and watershed algorithm can detect glistenings semi-automatically. [12] For those methods, the foreground extraction process is important to be accurate and the background images are required to be stable. In this paper, deep learning is applied to perform an automated glistening quantification using vitro images. The proposed methodology aims to differentiate between different number of glistenings lens and non-glistening lens in IOL. As a result, the doctors can proceed any appropriate treatment based on the occurrence of glistening in IOL. Deep learning is used from the initial step of training the raw input images to the final quantification.

Thus, overview of deep learning is described in section 2 and other sections are structured as follows: section 3 describes the methodology of this research and section 4 presents the result and discussion are followed as section 5.

## II. DEEP LEARNING

Deep learning (DL) is the subfield of machine learning and increase number of interesting in computer vision, speech recognition, natural language processing, object detection, and audio recognition. [13] Nowadays, many researchers in medical imaging contribute in the field of deep learning and become one of the methodologies for analyzing medical images. In addition, deep learning can provide the optimal solutions with good accuracy for medical imaging and is anticipated for future applications in health sector. [14]One of the most popular uses of the ML algorithms is probably quantification.

Although various DL architectures are emerged in recent years, Convolutional Neural Networks (CNN) is a common used architecture for complex operations which are required to use convolution filters. Neural Networks are essentially mathematical models to solve an optimization problem. [15] Typically, neural networks are biological inspired paradigm that enables computer to learn from data. Therefore, they are made of neurons, the basic computation unit of neural networks which have learnable weights and biases. [16] Each neuron receives some inputs, computes it on and produce a final output of neuron. Each neuron is connected to every neuron from the previous layer, but independently worked for single layer and do not share any connections. Training a neural network is finding the optimal weights resulting in the best quantification. CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers. [16] Glistening images are trained by using CNN and defined two classes as glistening and non-glistening as a result.

## III. Methodology

Our proposed methodology based on the CNN learning architecture for quantification where the classifier is identifying the glistenings in vitro images of IOL. This paper studies the feasibility of using deep learning for automatic glistening quantification by presenting a convolutional neural network that consists of multiple hidden layers with convolutional, max-pooling and fully connected layers. The advantages of CNN architecture are unnecessary of feature extraction process before being applied. The proposed methodology for quantification the glistenings in IOL images is as follows:

Step 1: Preprocessing
Step 2: Training by using CNN
Step 3: Quantification and Classification of Glistening and Non-glistening

### *A. Pre-processing*

There are two types of imaging for IOL: vivo and vitro. In this paper, the research was performed by vitro type image. All the received images from the hospital is about 20 images but glistenings are small and sizes are also varied. Moreover, the glistenings are distributed within IOL with different shapes. For instance, the following vitro images are glistenings inside IOL which were taken by using slit lamp.

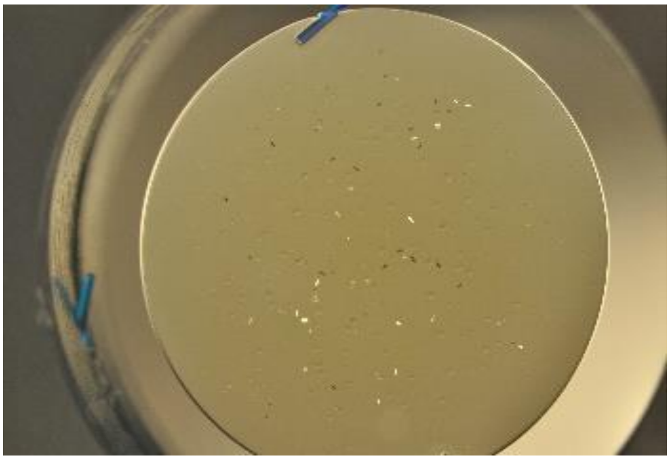

Fig 1: vitro images of IOL

Firstly, a good training dataset is required to be the robust model. The available images for training data is limited numbers and different shapes of glistenings are found in IOL. Convolutional neural network (CNN) is by all accounts the best machine learning model for image classification, [17] but in this case, we need many training examples to train it. In fact, many images are used for training to improve the accuracy and thus, we split each glistening from IOL by manually. Therefore, 1800 images of glistenings and non-glistening are acquired from these 20 images.

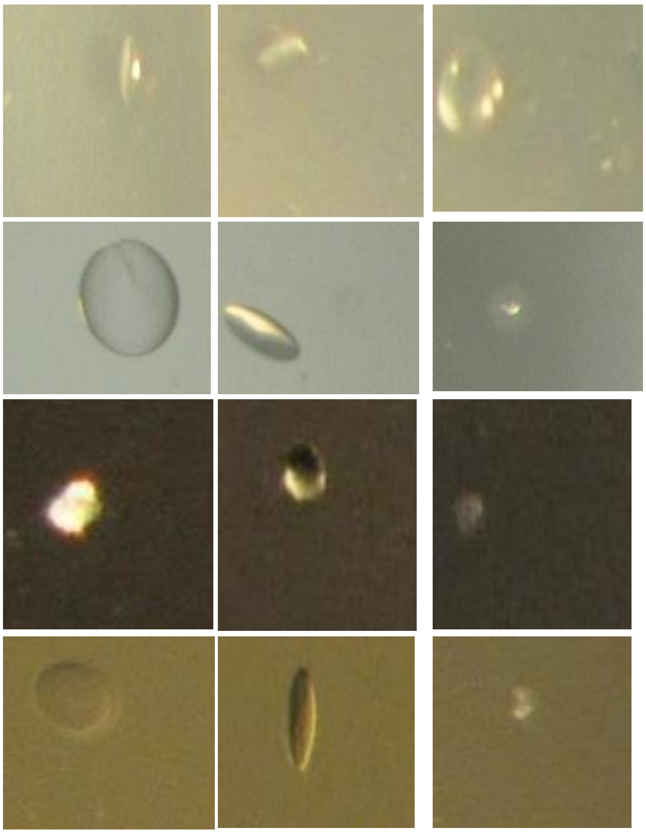

Fig 2: Different shapes of glistening for training

### *B. Training by using CNN*

Convolutional neural networks are a type of neural network and applied to image data. Every image is a matrix of pixel values. Typically, input data is divided into 3 parts:

1) Training data: 80% of splitted IOL images were used for training.
2) Validation data: The remaining 20% images were used for validation.
3) Test set: Different data for testing is prepared to evaluate and avoid Overfitting. Overfitting means neural networks work efficiently on the training data only but they cannot work correctly for other images. Because, it only works for our network on this validation data-set. Therefore, we also test set to be better accuracy of our model.

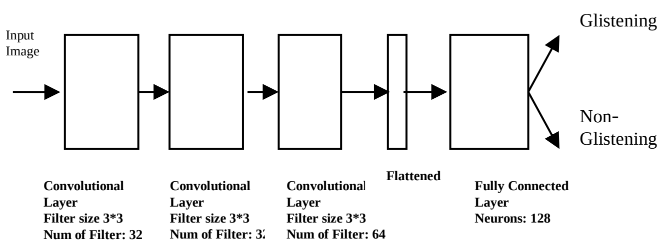


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Fig3: Glistening images are trained by CNN layers

In fact, CNNs consist of convolutional layers, pooling layers and fully connected layers. In a convolutional layer, the input image is convolved with one or multiple filters and the output is obtained from that layer and called an activation map which are a set of features. Next, a pooling layer in which the input is divided into small subsections and takes only the maximum value of that section as output. The final layers are fully connected layers and indeed, the classifier for output of the classification scores. We passed all glistening images of our splitted vitro IOL into these layers and results are shown in section 3.

### *C. Quantification and Classification of Glistening and Non-glistening*

When we attempt to build the classifier between glistening and non-glistening, we feed input images to neural network and find the optimal parameters. Hence, output layer pass out probability of glistening as 1 for all images of glistenings and probability of non-glistening as 1 for all images of non-glistenings. In training, all data are not fed to the network at once because we divide them into 32 small batches and it take 600 rounds (**iterations**) for complete data to be used for training. We use AdamOptimizer for gradient calculation and weight optimization and minimize cost with a learning rate of 0.0001.

However, features of the input image are acquired as the output from the convolutional and pooling layer. The purpose of the Fully Connected layer is to use these glistening features for classifying the input image into various classes based on the training dataset. Here, we use a softmax activation function of the fully connected layer and every neuron in the previous layer are connected to every neuron on the next layer.

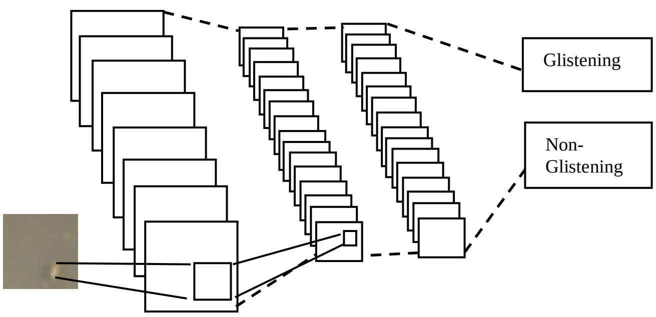


Fig 4: Fully connected layer to classify glistening or non-glistening

## IV. Result

In this paper, the input for this task is images of glistenings or non-glistenings from training dataset, while the output is the classification, accuracy on test dataset. Our task is to learn a classification model and to predict the decision for the training dataset. Frist, the objective of our training is to learn the correct values of weights/biases for all the neurons in the network that work to do classification between glistening and non-glistening. In fact, the initial value of these weights can be taken anything but it works better while taking normal distributions. Therefore, we calculate our model according to these values of weight/biases for all neurons and classify.

In this method, we finally observed the best accuracy 84.00% from classifier. To clearly understand how and why the CNN work, we have traced each epoch operation and how the result will change is shown with the following result. As a result, training accuracy is higher than validation. According to this result, we report training accuracy is moving forward in the right direction and improve accuracy in the training dataset.

TABLE I
Trained Result of Glistening quantification

| Training Epoch | Training Accuracy | Validation Accuracy | Validation Loss |
|---|---|---|---|
| 1 | 59.4% | 40.6% | 0.690 |
| 2 | 65.6% | 68.8% | 0.607 |
| 3 | 65.6% | 56.2% | 0.700 |
| 4 | 65.6% | 78.1% | 0.482 |
| 5 | 71.9% | 65.6% | 0.561 |
| 6 | 75.0% | 71.9% | 0.472 |
| 7 | 78.1% | 78.1% | 0.452 |
| 8 | 78.1% | 90.6% | 0.385 |
| 9 | 78.1% | 84.4% | 0.419 |
| 10 | 78.1% | 90.6% | 0.339 |
| 11 | 81.2% | 81.2% | 0.469 |
| 12 | 78.1% | 96.9% | 0.287 |
| 13 | 78.1% | 87.5% | 0.395 |
| 14 | 81.2% | 75.0% | 0.465 |

From the above table, we achieve the test-set with an accuracy of 81.2%. The result is impressive for our aim but it is important to visualize how our model is working. Therefore we use tensorboard to visualize the training results of running a neural net model with Tensorflow and especially, accuracy. A simple neural network is trained in TensorFlow and find some way to visualize the training and finally record summaries and track accuracy. The following figure is the accuracy of our training model and shows with the graph.

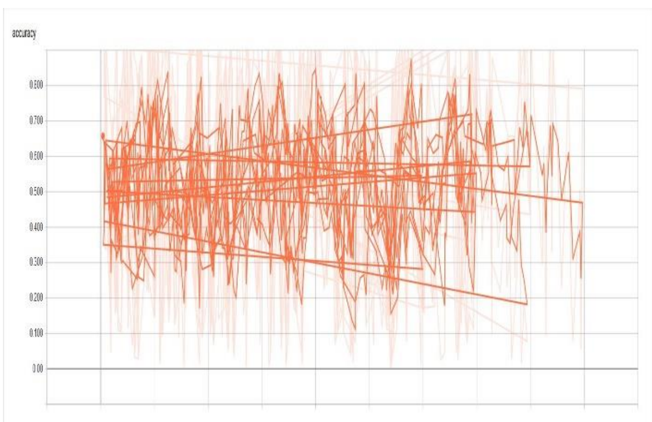


Fig 5: Accuracy of Training Model

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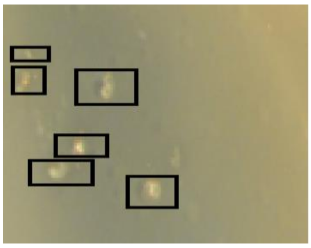
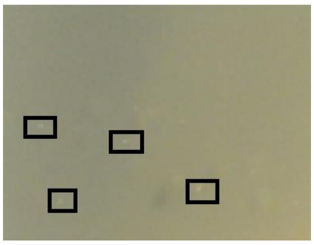
***Prediction***

We train all our images from the dataset and the parameters and architecture are saved as a model. Then, we load this model with the same network architecture and calculate the probability of the new image by applying softmax to the output of fully connected layer to evaluate whether test image is glistening or non-glistening. Therefore, the probability value can clearly classify and inform test image has glistening or not. The following image and probabilities values are from prediction algorithm after training the model.

[glistening : 0.5728693 non-glistening:0.42713067]



[glistening: 0.43124214 Non-glistening:0. 56875783]



## V. Conclusion

This paper proposed the quantification of glistening by using deep learning in medical imaging, including (1) background information of glistening detection (2) introduction of deep learning and CNN to glistening detection (3) quantification and classification of IOL images into glistening or non-glistening. We had presented and evaluated with convolution neural network for the task of automatic glistening classification. Compared to traditional machine learning methods, the main advantage of using deep learning models is that they can learn the most appropriate representation in a hierarchical manner as part of the training process. Since the proposed approach is only for classification, we will extend some object detection algorithms to achieve our goal.

Future research work will focus on clinical grading. All detected glistenings will be used in the calculation of its properties, namely, areas, distributions and densities in all 4 regions; whole lens, in 3mm zone, 4mm zone, and 5mm zone. [18] Our current result knows whether this IOL has glistening or not and clinical grading is not yet developed according to the number of glistening. In this report, we first briefly explained our motivation of this project and showed some background materials. Then, we precisely illustrated our task, including the learning task and the performance task. However, classification of glistening to perform clinical grading is progressing from current result.

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