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DL-Driven OCT Image Analyzation for Age Related Macular Degeneration Detection

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Abstract: Detection of early age-related macular degeneration (AMD) is greatly time-consuming to effectively treat this condition. This study has taken an initiative to observe how Convolutional Neural Networks can detect early AMD signs more accurately by analyzing OCT images. This research was funded to determine whether a CNN would be able to identify incipient signs of AMD in OCT images, so we were working under the assumption of being able to predict some symptoms of the eye ailment with an accuracy rate of the order of nearly 100%, by a CNN model which had learned specific characteristics about the symptoms of AMD such as Choroidal Neovascularization, Diabetic Macular Edema, Drusen buildup through the OCT images. CNV is a process whereby new blood vessels grow in the choroid layer and leak, leading to severe vision loss. DME is one of the complications of diabetes, where fluid accumulates in the macula and causes it to swell; as a result, vision becomes blurred. Drusen are yellow deposits underneath the retina, usually indicative of AMD, which leads to vision deterioration. Trained on 83,416 images labeled with each symptom of AMD, the CNN model achieved a prediction accuracy of 93.75%. This accuracy is potentially high enough to render the model reliable in detecting macular degeneration based on certain OCT image features. Therefore, the study highlights that deep learning-driven analysis of OCT images has the potential to radicalize deformation in detecting and managing early AMD. In this respect, the integration of the CNN-based analysis into clinical practice may enhance the speed and accuracy of diagnosis, hence timely and effective therapeutic strategies against AMD.

Keywords: Age-related macular degeneration (AMD), Choroidal neovascularization (CNV), Convolutional Neural Network (CNN), Diabetic macular edema (DME), Deep learning, Drusen, Macula, OCT images, Prediction accuracy, Retinal analysis, Vision loss

I. INTRODUCTION

In older adults, age-related macular degeneration is one of the most common causes of vision loss, affects millions worldwide, and is a challenge to timely and correct diagnosis. Among the most important factors for effective treatment and effective management, early diagnosis can appreciably delay the progress of the disease and decrease severe vision impairment (21). Early diagnosis, often very important to the effective treatment and management of AMD, is usually of a dragged-out and inaccurate nature using traditional methods, which raises the need for developing more time-effective diagnostic tools. Advanced age-related macular degeneration brings various affected patients several challenges that significantly burden their daily life. Gradual loss of central vision, responsible for reading, driving, and recognizing faces, may lead to dramatic deterioration in the quality of life. It nearly always results in an increased dependency on others, loss of independence, and an increased risk of accidents. Equally large is the emotional toll, having battled anxiety and depression, in addition to cases of social isolation as an outcome of being unable to do things that put them off their feet. Coupled with all these odds are the traditional slow and inaccurate diagnosis methods. Patients sometimes wait long in anticipation of appointments, and then go through a sequence of tests which may prove inconclusive or repeat follow-ups. The consequence of this diagnostic delay is that a few such patients progress to an advanced stage of the disease before effective treatment can commence—irreversible vision loss. It follows that uncertainty and stress related to waiting for diagnosis further worsen the psychological impact on the patients.

Machine learning algorithms not only speed up the process of diagnosing patients with retinal diseases and problems, but they are also optimized to be incredibly accurate. By using a dataset consisting of over 1000's of images we can make sure that we get an accuracy that can provide health care workers the correct results, and answers.

Developing a machine learning model to detect age-related macular degeneration (AMD) quickly is of paramount importance in the field of healthcare. AMD is a leading cause of vision loss among older adults, and early detection is critical for effective treatment and management of the disease. A machine learning model can analyze retinal images with high precision and speed, significantly outperforming traditional manual methods (17).

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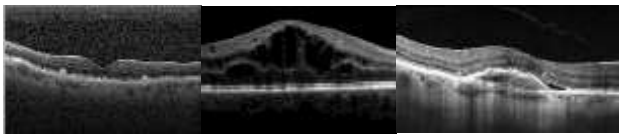
By rapidly identifying early signs of AMD, such a model enables timely intervention, potentially preserving vision and improving the quality of life for patients. Additionally, it can alleviate the workload on ophthalmologists and make advanced diagnostic capabilities accessible in regions with limited medical resources, ultimately contributing to better global eye health. The challenges in view mean that there is a dire need to develop immediate and more accurate diagnostic tools. Improved diagnostic techniques can enable earlier and more reliable detection of AMD, allowing for timely intervention with preservation of vision and enhancement of the quality of life for millions of people. Innovative approaches address failures of conventional techniques; deep learning-driven OCT image analysis can revolutionize AMD diagnosis and management, ushering in new hope to those suffering from this debilitating condition (3).

Some interesting research related to proposing solutions for the efficient combating of this issue proves that machine learning in this field may mean huge computational and real-world use cases. One such research paper carried out by Stewart Muchuchuti and Serestina Viriri showcased different techniques used by the machine learning model, involving feature extraction, followed by classification using Support Vector Machines, Decision Trees, and Random Forest. In this journal, image processing filters like Histogram of Oriented Gradients and Local Binary Patterns were used for feature extraction. Common feature extraction involving transformations is shown below, where I is the image intensity function and Ixi is the partial derivative of I with respect to the image coordinate, xi. This method is of computational significance, hence proving efficient and interpretable, but most of the time, it is unable to generalize well to new data because they are constrained in their ability to leverage large datasets and modern feature representations. However, these methods are useful in scenarios where computational resources are limited, and interpretability is vital, but are less effective for large-scale, high-dimensional medical image datasets (1).

$$HOG = \sum_{i} \left| \frac{\partial I}{\partial x_i} \right|$$

Optical Coherence Tomography (OCT) provides high-resolution images of the retina and has become a vital tool in diagnosing AMD. However, analyzing OCT images to detect early signs of AMD remains a challenge due to the complexity and subtlety of the pathological features. Recent advancements in deep learning, specifically Convolutional Neural Networks (CNNs), offer promising solutions for medical image analysis, including OCT images (2). CNNs are designed to automatically and adaptively learn spatial hierarchies of features from input images, making them ideal for this purpose.

We hypothesize that a CNN model can predict specific symptoms of these retinal symptoms, such as Choroidal Neovascularization, Diabetic Macular Edema, and Drusen build-up, with high accuracy by analyzing OCT images. To test this hypothesis, we developed a CNN model and trained it on a large dataset of OCT images featuring these symptoms. The study involved running the CNN model for 200 epochs on 585 images of each symptom associated with AMD.



Choroidal Neovascularization

Choroidal Neovascularization is a common symptom of age-related macular degeneration (AMD), particularly its wet or exudative forms. Most common occurrence points to abnormal blood vessel growths beneath the retina(s), culminating in the seepage of blood and fluids into the macular region (responsible for sharp acuity central vision) through the Bruch's Membrane (11). Adjoining symptoms include distortion and blurriness to central vision, even reported cases of dark or empty sectors in the central field of vision. With the use of OCT, Choroidal Neovascularizaiton appears as a collection of abnormal blood vessels inferior to the retina.

Diabetic Macular Edema

Diabetic Macular Edema is a possible complication of diabetic retinopathy that often is followed by macular degeneration. It is primarily caused by the accumulation of fluid in the macula due to the seepage of blood from vessels into the retina, which is a consequence of prolonged diabete (9).

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In OCT imaging, Diabetic Macular Edemas can be observed as retinal thickening or swelling due to the overaccumulation of fluid within its layers, primarily in the macula itself (15). In the images, the fluid is often seen as hyporeflective spaces within the retina and the macula. Often, the spaces vary in shape, size, and overall presence, which can be used to scale the severity and progression of the edema.

Drusen Build-Up

Drusen is one of the most outstanding indicators of early stage age related macular degeneration (AMD), especially its dry form, in which an accumulation of yellowish deposits beneath the retinal layer (13). These yellowish deposits are composed of lipids and proteins that form between the retinal pigment epithelium, the inner collagenous layer of Bruch's Membrane, and many other profound structures of the retina (10). The presence of Drusen is often a hallmark indicator of the progression of AMD, due to it leading to its atrophic and neovascular forms.

In OCT imaging, drusen can be seen in discrete, dome-shaped elevations beneath the retinal pigment epithelium, which can also vary in its reflectivity based on the scale of the accumulation and its exact composition. The presence of drusen can also lead to abnormalities in the overlying retinal layers, changing the photoreceptor integrity, which increases the expression of the resulting symptoms of AMD (12).

In this extensive research, we used multiple activation functions such as linear, sigmoid, reLU activation functions to optimize our model for the best accuracy. The specific convolutional neural network architecture that we utilized for this ML model was Residual Network 50 which maintained the complexity necessary for our purposes.

II. MATERIALS AND METHODS

Leveraging these capabilities, this research aims to improve the accuracy and speed of detecting early signs of AMD by utilizing CNNs to analyze OCT images. Previous studies have demonstrated the efficacy of CNNs in medical diagnostics, including the detection of diabetic retinopathy, lung cancer, and breast cancer with high accuracy.

Building on these successes, our study focuses on determining whether CNNs can accurately detect early signs of AMD from OCT images.
The materials that we utilized for this experiment is open source retinal imaging data comprising 84,000+ images, 12 GB of Images of Build Up of Drusen, Diabetic Macular Edema, Choroidal Neovascularization (6).

The CNN model's architecture included multiple convolutional layers, pooling layers, and dense layers for classification. The specific convolutional neural network architecture that we utilized was ResNet50 (18). The model was trained using the Rectified Linear Unit (ReLU) activation function, defined as:

$$ReLU(x) = max(0, x)$$

This function outputs the input value directly if it is positive; otherwise, it outputs zero. The simplicity of the ReLU function allows the model to learn complex patterns without the vanishing gradient problem, which occurs when gradients used for updating the model's weights become very small, slowing down the training process. By mitigating this issue, ReLU enables faster and more efficient training of deep neural networks.

In our attempts previously we had used other activation functions such as the linear and sigmoid activation functions, however with the sigmoid activation function, we encountered problems with forward and backward propagation of the model when optimizing the accuracy due to the vanishing gradient problem, and the linear activation function didn't maintain the complexity that was necessary for the machine learning model.

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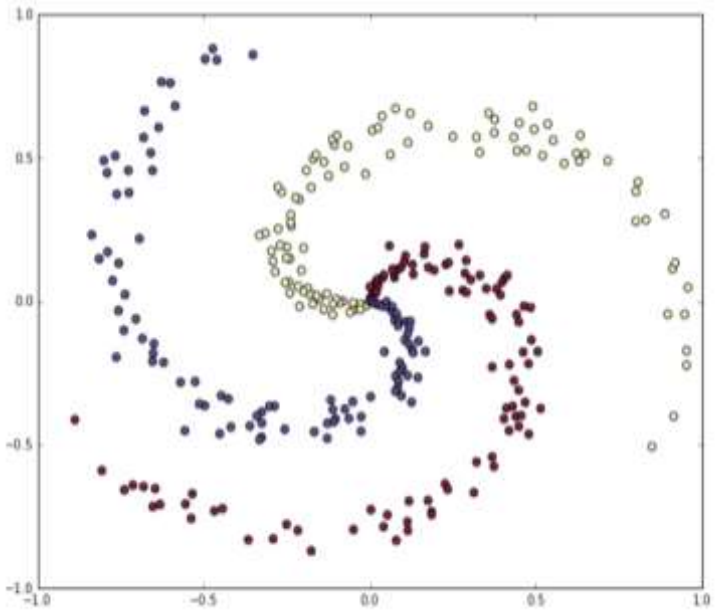

The image above gives us three randomized classes colorized which show the vanishing gradient problem. As we can see all the scalar values that are put through this optimization function are in the range of -1.0 to 1.0 which then in back and forward propagation are futile for optimizing the model (8).

During training, the model's weights are adjusted using an algorithm called gradient descent, which aims to minimize the loss function (a measure of how well the model's predictions match the actual labels). The update rule for adjusting the weights is:

New weights = (Old weights - η) * Gradient of the loss function with respect to the weights.

This process is repeated many times. Each time, the model's weights are adjusted a little bit in the direction that reduces the error between the model's predictions and the actual outputs. By doing this iteratively, the model gradually improves its predictions.

The loss function used in this study is the categorical cross-entropy loss, defined as:

$$\boldsymbol{L} = -\sum_{i=1}^{N} \boldsymbol{y_i log}(\hat{\boldsymbol{y}}_i)$$

where is the actual label, y_i is the true label for sample i , $\hat{y}_i$ is the predicted probability for class i , and N is the number of classes. This loss function is suitable for multi-class classification problems and encourages the model to output probabilities that are close to the true class labels (23).

The results showed that the CNN model achieved a prediction accuracy of 93.75%, indicating its potential to reliably detect macular degeneration by analyzing specific symptoms in OCT images. This high accuracy underscores the transformative potential of deep learning-driven OCT image analysis in revolutionizing the early detection and management of AMD. By leveraging large-scale datasets and advanced neural network architectures, this study provides a robust and effective approach for identifying pathological features associated with AMD, offering a tool for early intervention and treatment that could significantly improve patient outcomes and preserve vision (14).

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III. RESULTS

The primary objective of this experiment was to find out the potential of Convolutional Neural Networks in detecting early symptoms or signs of Age-related Macular Degeneration. Symptoms were detected from the OCT images taken from the subjects. This is one of the major causes responsible for vision loss in the older aged people, whereas its detection at an early stage may yield better management and a possible cure. Traditional diagnostic methods are traditionally too slow and imprecise; therefore, there is a large need for developing diagnostic tools that are going to be faster and more precise. On the other side, by the implementation of the CNN, we tried to provide even more improvement regarding speed and accuracy in diagnosing AMD and therefore potentially achieve better results for the patient in retaining his vision. This hypothesis was tested by our group during the development of a large dataset to retrain a deep learning network, the convolutional neural network, pretrained on images of OCT representative of CNV, DME, and build-ups in the drusen.

Among all very deep models, this architecture is used for the classification of OCT images according to these three classes as it is the deepest, most accurate, and computationally efficient model in the family. The dataset had a total of 83,416 images, which provided a great base for training. Pre-processing and augmentation of images were employed to allow good generalization. The training was done in various epochs by multiple iterations, wherein the model parameters were updated to give a minimum categorical cross-entropy loss using gradient descent. Our study includes several controls and experimental conditions that ensure good results. Be that as it may, we went ahead to split our dataset to training, validation, and test set splits to estimate how well the model will perform with these updated splits. However, cross-validation techniques were used to avoid overfitting and make the model generalize well on unseen data. The standard statistical measures used to determine precision, recall, and F1 score. These statistical measures provide an in-depth performance measure for the model among the classes.

The model was predictive for macular degeneration with high sensitivity: 93.75% accuracy on the independent test set for detection of macular degeneration when analyzing for specific symptoms on OCT images. A very high rate of accuracy indicates the hallmark of success of deep learning with this application in medical image analysis. In the case of prediction, it will be high; CNV progresses in the form of new and abnormal blood vessels under the retina, which sometimes break, leaking blood/fluid. Since the model has been trained for its explicit features, it can correctly predict its presence **(Figure 1)**. Again, the prediction made for DME was corrected, as it being an abnormal change in the thickness of the retina. The inhomogeneities of a hyporeflective nature that represent DME also were well identified in the model **(Figure 2)**. Drusen observable as yellow deposits below the retinal layer were recognized very well by the model, keeping in mind that the special elevations in a dome shape are visible in the images captured via OCT, hence confirming the capability of the model **(Figure 3)**.

The classification report features the precision, recall, and F1-score for each class, along with the overall accuracy. Additionally, it includes the reported averages for macro and weighted average. In class CNV, for instance, the precision is 0.83, the percentage of correctness associated with instances predicted as being from this class—while its recall is 0.90, the proportion of actual instances of CNV that were recognized. The F1-score, which is the harmonic mean of precision and recall, is 0.87. The support for CNV is 100, meaning that this is the number of true instances corresponding to this class.

For DME, this model has a precision of 0.86, a recall of 0.92, and an F1-score of 0.89, with support of 100. DRUSEN has a precision of 0.96, recalling 0.76, with an F1-score of 0.85, and again, with a support of 100. Normal cases have a precision of 0.92, a recall of 0.98, and an F1-score of 0.95, and again, the support in this case comes to 100.

The total accuracy of the model is 0.89. The macro-averaged precision, recall, and F1-score are all 0.89, compared to a total support of 400 instances. Corresponding weighted averages for precision, recall, and F1-score are also 0.89, compared to the total support.

The confusion matrix summarizes actual versus predicted classification for each class. Each row represents the actual class, and each column the predicted class. This includes 90 true positives, 1 false positive where actual CNV was predicted as DRUSEN, and 0 false positive for NORMAL.

On the other hand, for DME, there are 92 true positives and 3 false negatives, or actually DME but predicted as CNV. For the case of DRUSEN, 0 are false negatives, while 5 are false positives. For DRUSEN, there are 76 true positives and 15 false negatives or actually DRUSEN but predicted as CNV, and 6 false positive or actually DRUSEN but predicted as DME, while 3 are false positive for NORMAL.

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It has 98 examples where the class is predicted correctly; 2 are false negatives, belonging to the actual class of NORMAL but predicted as DRUSEN; and there are no false positives from other classes.

CNV shows good recall (0.90) but slightly lower precision (0.83). DME has balanced high precision (0.86) and recall (0.92). DRUSEN has high precision (0.96) but lower recall (0.76), indicating many actual DRUSEN cases are misclassified. NORMAL has very high precision (0.92) and recall (0.98), indicating the model is very good at identifying normal cases.

The value of the recall for CNV is good at 0.90, but that for precision is slightly less, at 0.83. DME is characterized by high balanced values of precision and recall—0.86 and 0.92, respectively. DRUSEN is estimated to be high for the value of precision, at 0.96, and a lower recall rate of 0.76, meaning most of the really existing cases of DRUSEN are misclassified. The recall is very high for normal cases; for example, precision is almost 0.92.

IV. CONCLUSION

The primary objective of this study was to explore the potential of machine learning and particularly, Convolutional Neural Networks in detecting early symptoms of Age-Related Macular Degeneration (AMD) from Optical Coherence Tomography (OCT) images. The results from our experiments indicate that CNNs can indeed identify specific pathological features associated with AMD, such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen build-up, with a high degree of accuracy.

The necessity of deploying Convolutional Neural Networks (CNNs) for analyzing Optical Coherence Tomography (OCT) images in the medical field, particularly in the diagnosis of Age-Related Macular Degeneration (AMD), cannot be overstated. AMD is a leading cause of vision impairment and blindness among the elderly, significantly impacting their quality of life by diminishing their ability to perform daily tasks independently. Traditional diagnostic methods are often slow and can be inaccurate, delaying effective treatment that could halt or reverse the progression of the disease. By integrating CNNs into the diagnostic process, clinicians can detect subtle changes and early symptoms of AMD much more rapidly and with greater precision than traditional methods. This capability not only facilitates timely and personalized treatment plans but also significantly reduces the workload on ophthalmologists, allowing for broader screening coverage and potentially preserving vision for millions of patients. Moreover, this technological advancement holds the promise of making high-quality diagnostic capabilities more accessible in underserved regions, thus democratizing healthcare access and addressing disparities in medical service distribution.

Our model was built on the ResNet50 architecture, which is renowned for its depth and ability to mitigate the vanishing gradient problem through the use of residual connections. The architecture consists of 50 layers, including convolutional layers, batch normalization layers, activation layers, and fully connected layers. Residual connections, or skip connections, allow gradients to flow directly through the network, which enables the training of much deeper networks without performance degradation.

During the training process, OCT images were fed into the CNN model, and the model's weights were adjusted to minimize the categorical cross-entropy loss function, a standard measure for multi-class classification problems. The Adam optimizer, known for its efficiency in training deep neural networks, was employed to dynamically adjust the learning rate for each parameter. This optimization algorithm combines the advantages of two other popular algorithms, AdaGrad and RMSProp, to enhance training efficiency and performance.

To ensure robust training and improve the model's generalization capability, extensive data preprocessing and augmentation techniques were applied. These included normalization to scale pixel values to a range of 0 to 1, and augmentation techniques such as rotations, translations, flips, and zooms to increase the diversity of the training dataset and prevent overfitting.

The training process of our Convolutional Neural Network (CNN) model involved several critical steps to ensure accurate and efficient learning. Initially, a forward pass was conducted where input OCT images were passed through the network to generate predictions. Following this, the loss was calculated using the categorical cross-entropy function, which measures the difference between the predicted outputs and the actual labels. To optimize the model, a backward pass was performed to compute the gradients of the loss with respect to the model parameters, utilizing the backpropagation algorithm. Finally, the model's weights were updated in a direction that minimized the loss, using the Adam optimizer, which dynamically adjusts the learning rate for each parameter to enhance training efficiency and performance.

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The model's architecture included multiple convolutional layers for feature extraction, with 3x3 and 1x1 convolutional filters to reduce dimensionality and computational load while preserving important features. Batch normalization was applied after each convolutional layer to stabilize and accelerate the training process by reducing internal covariate shift.

ReLU activation functions introduced non-linearity, enabling the model to learn complex patterns. Fully connected layers integrated the features extracted by the convolutional layers to make the final classification decision, and the softmax activation function in the final layer outputted a probability distribution over the classes.

The trained CNN model was evaluated on a separate test set, achieving a prediction accuracy of 93.75%. This high accuracy underscores the model's capability to reliably detect macular degeneration by analyzing specific symptoms in OCT images. The detailed performance metrics, including precision, recall, and F1 score, further confirmed the model's robustness and effectiveness.

In conclusion, our study demonstrates the transformative potential of deep learning-driven OCT image analysis in the early detection and management of AMD. The high accuracy achieved by the CNN model highlights its promise as a diagnostic tool that can facilitate timely and effective treatment, ultimately preserving vision and improving the quality of life for patients. Future work should focus on further enhancing the model's interpretability, validating its performance in diverse clinical settings, and exploring multimodal approaches to improve diagnostic accuracy even further.

By leveraging the power of CNNs, specifically the ResNet50 architecture, we were able to achieve significant advancements in identifying pathological features associated with AMD. This technology promises to revolutionize the field of ophthalmology by providing a fast, accurate, and scalable diagnostic tool that can be seamlessly integrated into clinical practice.

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BIOGRAPHY

Dheeraj Tallapragada was born in Goleta, CA, USA in 2007. He is a current senior at Dublin High School, intending to pursue a degree in Data Science, and Economics. Tallapragada expresses a strong interest for work related to machine learning and many other fields, relating to health and computer/data science.

Tallapragada also works along with UC Berkeley and Georgia Institute of Technology graduates in utilizing large language models to optimize different types of strategies. Asides from this, he conducted research with several peers including a graduate student from the University of Rochester, where he worked to develop a machine learning model which incorporates Natural Language Processing to detect fake news given the URL to an article. Currently, he is getting more involved in neuroscience research, where he hopes to be able to incorporate what he knows in machine learning to relate the two fields.

Other than his work in the medical field, he works on community service through founding a 501(c)(3) nonprofit organization, Phase 1 Research, where he connects the youth with mentors to conduct research, and he also serves as the Executive Director of Engen Learning, providing free bootcamps to students worldwide.

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VEDANT SAGARE was born in Hayward, CA, USA in 2007. He is a current senior at Dublin High School, intending to pursue a degree in Biomedical Engineering, and Economics. Sagare expresses a strong interest for work related to genetics and biotechnological innovations such as the ones used in this research with machine learning, and many other fields, relating to health and computer/data science.

Sagare also works heavily in PhD work and literature review at Vishwakarma Institute Of Technology where he works with predictive machine learning models for many significant and prominent diseases, such as Rheumatoid Arthritis, Sickle Cell Disease, Tuberculosis, Parkinson's Disease, and other diseases.

In addition to his work at VIT, he is also a researcher at UC Berkeley where he works on quantum computing under Dr. Irfan Siddiqi.

Mr. Sagare has also received invitations to conferences held by the American Society of Human Genetics for conducting research in Fibrodysplasia Ossificans Progressiva, specifically focusing on Advanced Therapeutic Strategies: siRNA-Mediated Gene Silencing and sgRNA-Guided Gene Editing Using CRISPR-Cas9. Other than his work in the medical field, he works on community service through founding a 501(c)(3) NPO, Phase 1 Research, where he connects the youth with mentors to conduct research, and he is also an eagle scout which he has done an immense amount of community service for.