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AutoML-based neural network for the detection of Keratoconus

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Abstract. For many years, the diagnosis of Keratoconus (KCN) has heavily relied upon the expertise and subjective judgment of clinicians. However, this study represents a pioneering effort to revolutionize KCN identification through the integration of Convolutional Neural Network (CNN) classification. In this innovative approach, the model is specifically designed to process corneal images as its primary input data, categorizing them into one of three distinct classes: "KCN," "suspect," or "normal." Remarkably, this CNN model, meticulously implemented on the Edge Impulse platform, has achieved an astounding accuracy rate of 98.2% in correctly identifying KCN cases. Nevertheless, there remains substantial potential for improvement in the accurate classification of the "suspect" and "normal" categories. In conclusion, this study exemplifies the vast potential of CNNs to transform the diagnosis of keratoconus. With ongoing refinements, including enhanced data preprocessing, attention mechanisms, and quantitative integration, this approach could herald a transformative era in KCN identification and management.

Keywords: Artificial Intelligence, Keratoconus, Convolutional Neural Network.

1. Introduction

The definition of Artificial Intelligence (AI) is a field of science and engineering concerned with the computational understanding of what is commonly called intelligent behavior, and with the creation of artefacts that exhibit such behavior. Researchers have also been exploring ways to apply AI in every field. During the initial stages of AI development, its capabilities were confined to basic tasks due to computational constraints. This led to periods of frustration among individuals. Nonetheless, with significant advancements in integrated circuit technology and the emergence of Moore's Law, AI has experienced a transformative phase. As computers get faster and faster, the structure of AI models is becoming more complex. At the same time, further theories and better algorithms have been continuously proposed. In this context, AI is becoming increasingly powerful and more widely used due to the characteristics of computer.

Nowadays, AI is involved in various fields in people's daily lives, especially for the medical domain [1, 2]. For instance, one reported study tried to use computer to diagnose acute abdominal pain. Recently, AlphaFold database was built by using AI to predict protein structure in order to develop new drugs and they have met a highly positive result [3]. AI is used to take care of patients because it is more attentive and available 24 hours a day [4] or used to facilitates doctors in diagnosing disease [5-7]. AI has been used to process medical images that were once impossible to process with the computing power once

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available. Looking for visual symptoms is one of the most intuitive methods in the diagnosis process. In the diagnosis of some diseases has obtained more than 90 percent accuracy [8].

In this paper, the author tried to use a deep learning network which implemented on Edge Impulse to identify Keratoconus (KCN). The exact origins of keratoconus remain uncertain, although it is believed that a combination of genetic and environmental influences contributes to its development. Notably, about 1 in 10 individuals diagnosed with keratoconus have a parent who also experiences the condition. In KCN, the patient's cornea thins and gradually bulges outward into a cone shape. A cone-shaped cornea causes blurred vision and can cause sensitivity to light and glare. Keratoconus generally affects both eyes. However, it can affect one eye more than the other. It normally begins to affect people between the late teens and 30 years of age. The condition may progress slowly for a decade or longer. In the early stages of keratoconus, patients might be able to correct vision problems with glasses or soft contact lenses. Later, the patient may have to be fitted with rigid, gas permeable contact lenses or other types of lenses, such as scleral lenses. If the patient's condition worsens, a cornea transplant may be needed. The model is trained with 2961 224x224 corneal images and has three outputs: KCN, suspect, and normal. Although the overall accuracy is 76.1%, as one of the outputs is "suspect", if a sample is "KCN" but classified as "suspect", the patient would go to hospital for a double check by doctor. In this case, the accuracy of output "KCN" is 98.2%.

2. Method

2.1. Dataset description and preprocessing

In this project, dataset used is the Keratoconus detection dataset provided by Kaggle [9]. the dataset contains 4011 images in total, divided into train validation set and test set, which has 2961 images and 1050 images respectively. The images are arranged in sets of seven. The training validation set comprises 150 sets of normal corneal maps, 150 sets of KCN (Keratoconus) corneal maps, and 123 sets of suspected corneal maps. In the test set, there are 50 sets for each class.

The preprocessing procedure comprises two main segments. Initially, the image was resized to dimensions of 96 x 96. The chosen resize mode was "squash" since certain valuable features could be located at the image's edges (as illustrated in figures 4 and 5), thus preventing any cropping of the image.

2.2. Proposed method

The model was implanted on Edge Impulse [10] platform. It takes several steps to build the model. Edge Impulse is a platform that facilitates the development and deployment of machine learning models for edge devices. It aims to enable developers to create and implement machine learning algorithms on low-power devices like microcontrollers and sensors, often referred to as "edge devices." These devices process data locally, rather than relying on sending data to the cloud for analysis, which can be beneficial for privacy, real-time processing, and reducing latency. It provides tools for data collection, preprocessing, model training, and deployment, all tailored for resource-constrained devices. It supports a wide range of applications, including predictive maintenance, anomaly detection, audio and image recognition, motion detection, and more.

After the data was updated, user can build their model by adding boxes, as shown in Figure 1. After updated the data, Edge Impulse will generate features by itself, and the distribution of samples will be shown in a graph (Figure 2) which allow users have an intuitive understanding of the distribution of data. The last step was choosing model and setting model parameters.

There are several parameters available as shown in Figure 3. The model used is MobileNetV2 96x96. MobileNet stands as a family of efficient convolutional neural network (CNN) architectures designed with a focus on lightweight design and suitability for mobile devices and those with restricted resources. The primary objective behind MobileNet's development was to facilitate real-time, on-device deep learning inference while keeping computational demands and memory requirements to a minimum. These architectures have been particularly fine-tuned for tasks like image classification, object detection, and various other computer vision applications. The cornerstone of MobileNet's approach lies in its use

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of depthwise separable convolutions. Unlike conventional convolutional layers that combine spatial convolutions (across channels) and depthwise convolutions (across spatial dimensions), depthwise separable convolutions break these two types apart. This division results in a notable reduction in computational complexity and model size. As a result, MobileNet models shine in scenarios where processing power and memory are constrained, as is common with devices such as smartphones, IoT devices, and embedded systems. MobileNet encompasses various iterations, each with distinct configurations and levels of efficiency. For instance, MobileNetV1 introduced the concept of depthwise separable convolutions. Subsequent versions like MobileNetV2 and MobileNetV3 refined the architecture even further, enhancing accuracy and integrating features like inverted residuals and linear bottlenecks. Parameters used are 64 final layer neurons; 0.1 dropout rate; 0.0005 learning rate and was trained for 20 training cycles.

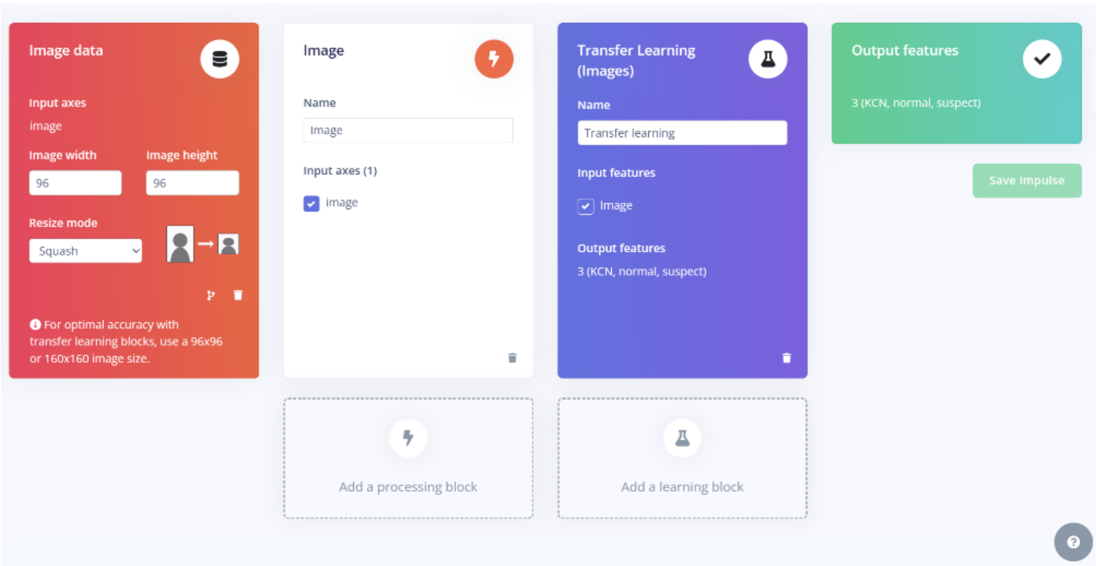

Figure 1. Adding learning box.

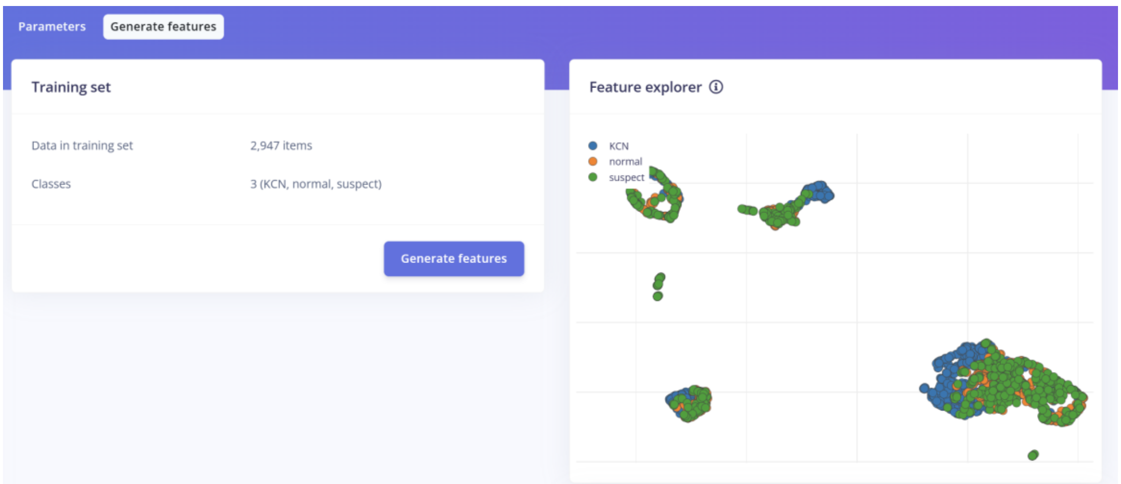

Figure 2. Distribution of sample in dataset.

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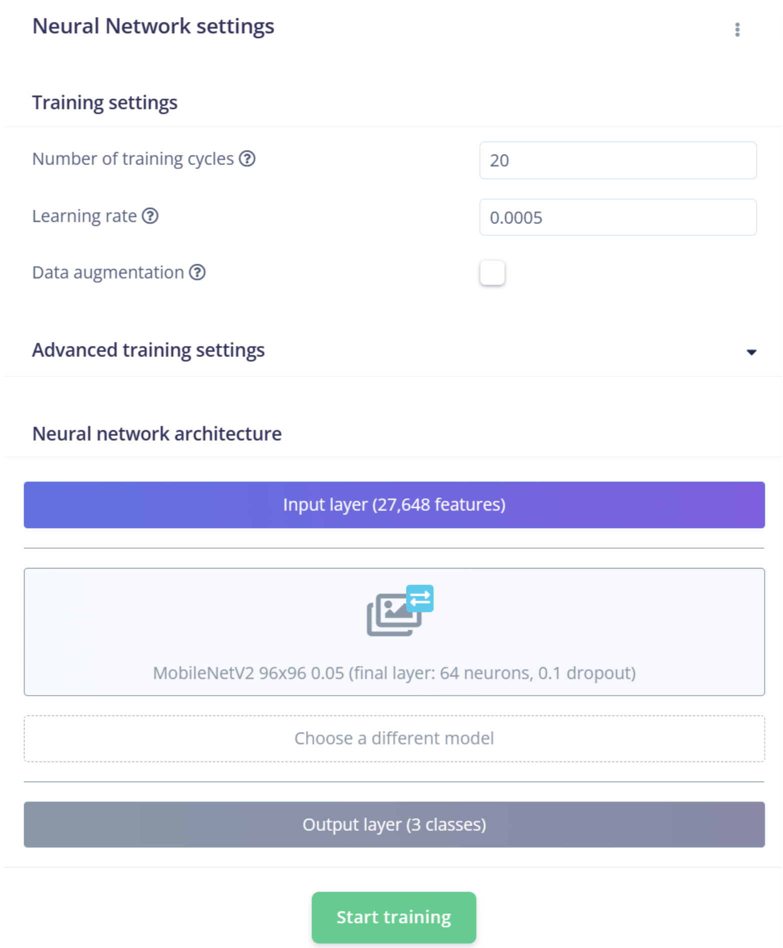

Figure 3. Parameters of the model.

3. Results and discussion

Figure 4 is the confusion matrix of the model, which illustrates the performance of model on each class. It is clear that the model works well on KCN class. However, the model's accuracy on class suspect is only 46.8%. Although the "suspect" class contains uncertainty itself, but every time the model predicts a sample with label "suspect" to "normal", it may cause a patient missed the optimal treatment time.

Confusion matrix (validation set)

	KCN	NORMAL	SUSPECT
KCN	92.5%	1.8%	5.7%
NORMAL	2.4%	80.5%	17.1%
SUSPECT	10.1%	43.0%	46.8%
F1 SCORE	0.92	0.75	0.53

Figure 4. Confusion matrix.

Although the model has a positive performance on KCN class, but there are still room for improvement in "suspect" class and "normal" class. also, current models lack interpretability. The output of each input sample can be clearly obtained, but the basis for the classification of the model is still vague. The feature explorer illustrates the predict of model on every sample. In Figure 5, most of

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incorrect predicts happen in the area of normal and suspect. As shown in Figure 6, most of "normal" sample and "suspect" sample are mixed together, which causes the performance of classification of "normal" sample and "suspect" sample difficult. Figure 7 shows two example of similar sample from "normal" class and "suspect" class. Because although KCN in the middle and late stages is easy to diagnose because of severe corneal deformation, for the early stage of keratoconus, the results of optometric vision examination are easily confused with other refractive errors (myopia, hyperopia, astigmatism, etc.), and there is no special obvious corneal morphological change. Therefore, it is not only unable to be used as a diagnostic method, but also often misdiagnosed as an important cause of non-keratoconus, such as ametropia, amblyopia, keratitis, etc.

The author also suggested further steps to improve the model. Firstly, more preprocessing can be done before samples used for train. The outer text in the data is useless for class identifying, so those can be cut and only left the central part of the image, or ask an experienced physician for diagnostic criteria to highlight certain parts of the image or split the image to judge each part separately and then synthesize the results. On the other hand, the model itself may be improved by several methods. New Attention Mechanism may be introduced to make the model focus on relevant features of greater significance. Furthermore, incorporating quantitative analysis into the current model could prove advantageous. Notably, Maeda and Klyce achieved commendable outcomes solely through quantitative analysis [11]. The model's inquiries can be interpreted. In 2016, Macro and others proposed a viable solution [12] by employing the black box model to train a concise yet explanatory model, thereby elucidating the black box model through this simplified approach.

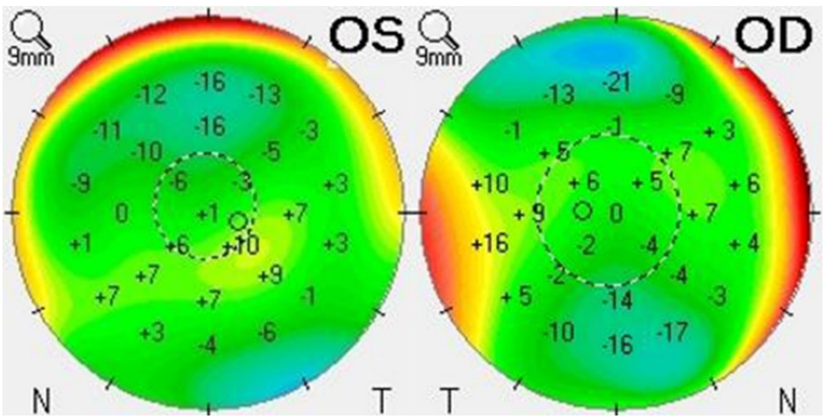

Figure 5. Normal corneal image: left; suspect corneal image: right.

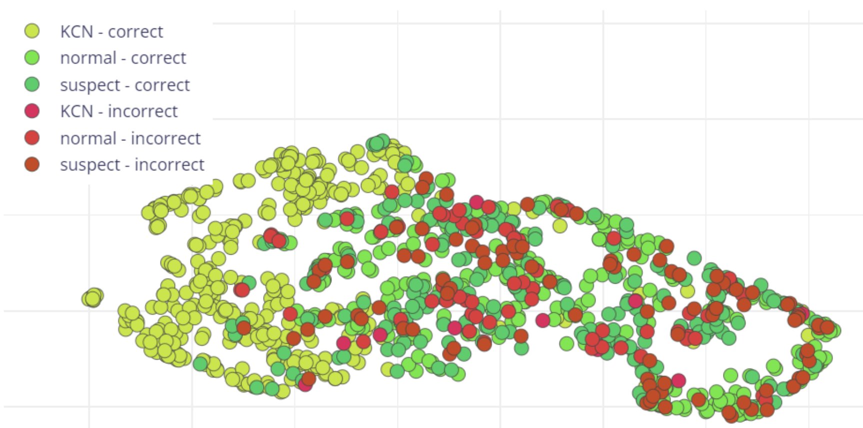

Figure 6. Result distribution.

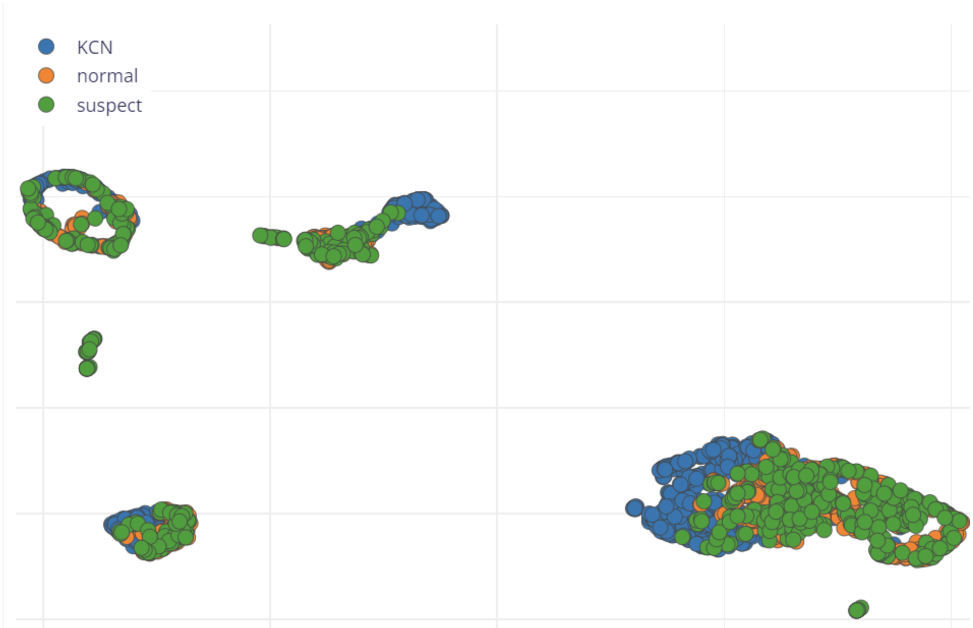

Figure 7. Feature distribution.

4. Conclusion

In this study, the author aimed to employ a CNN model for KCN identification using corneal topography images as the sole input. The implementation of the model was carried out on the Edge Impulse platform, which facilitates code-free construction of CNN models. The achieved accuracy in identifying KCN samples reached 98.2%; however, performance was comparatively lower for both the 'suspect' and 'normal' classes due to their similarity caused by subtle manifestations during early stages of KCN development that can be misdiagnosed as other ocular conditions. To enhance model performance, several approaches are suggested including excluding irrelevant image components or emphasizing crucial features, as well as refining the model itself through incorporation of improved attention mechanisms with expert medical guidance or integration with quantitative methods.

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