Keratoconus Classifier for Smartphone-based Corneal Topographer

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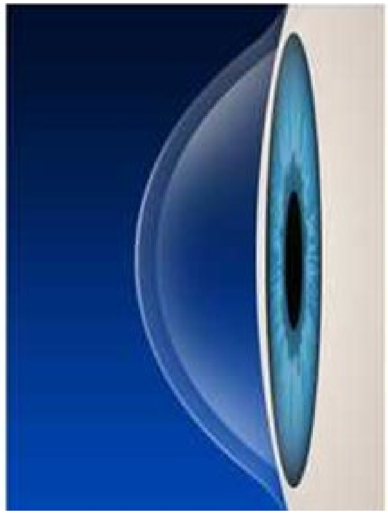
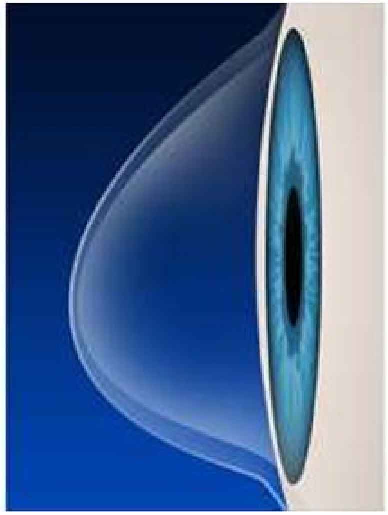
Motivation

- **Keratoconus** (KC): causes deformed cornea.
- Affects people aged 10-25 years, leading to (partial/complete) **blindness**.
- 2.3% in global south vs 0.05% in USA.
- In 2012, 27% of corneal transplants worldwide were to treat KC.
- Diagnosis requires expensive & bulky medical devices that increases inaccessibility.



Healthy Cornea



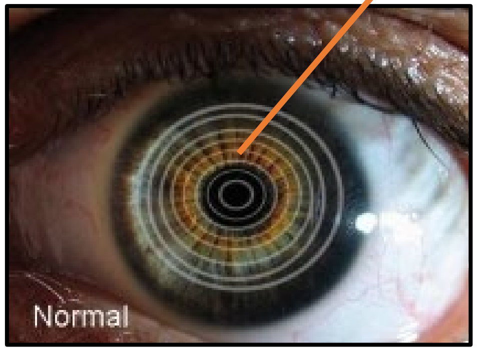
Keratoconus Cornea

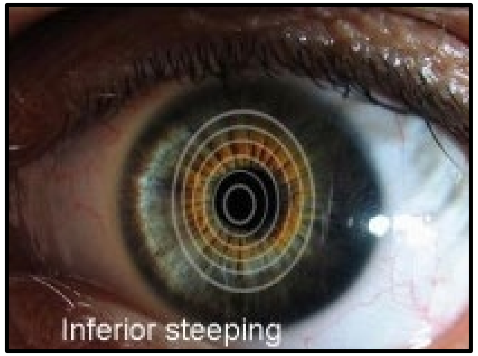
Keratoconus Diagnosis

Handheld Placido Disc

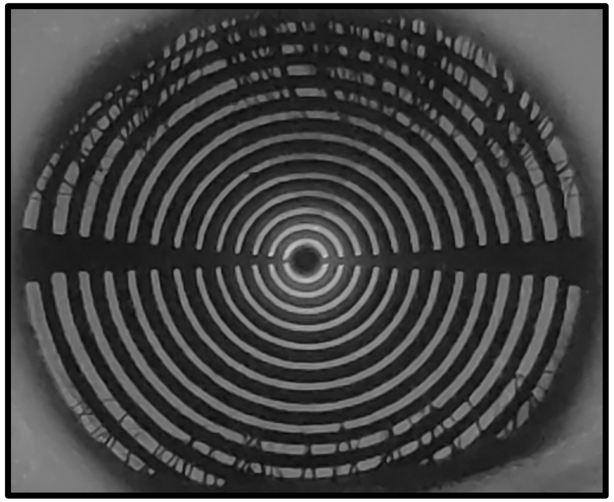
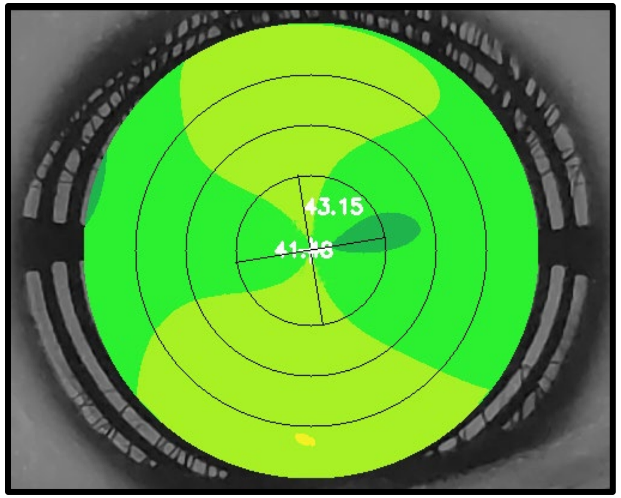
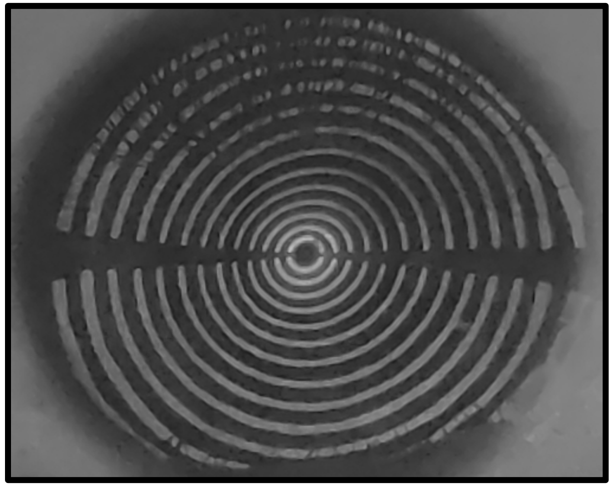
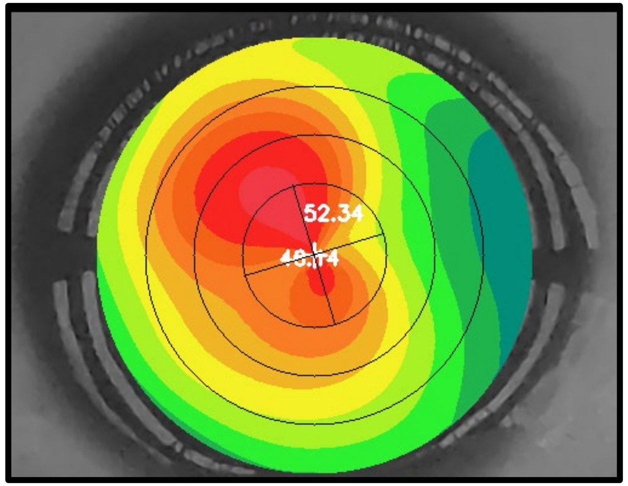
Corneal Topographer

Mires



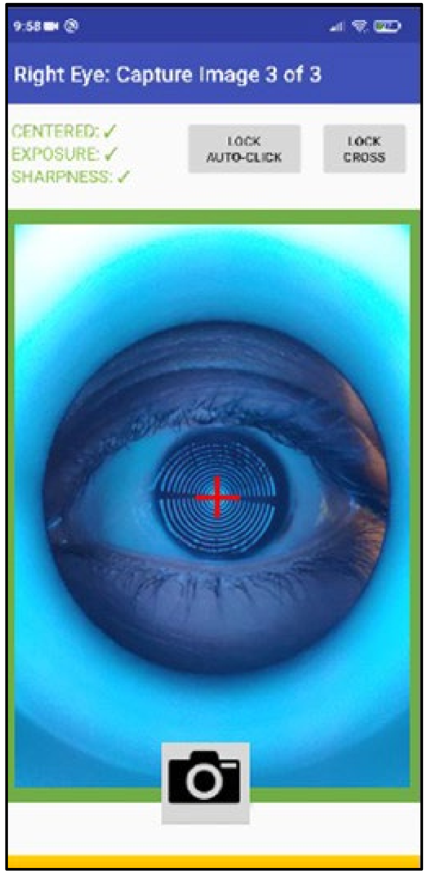


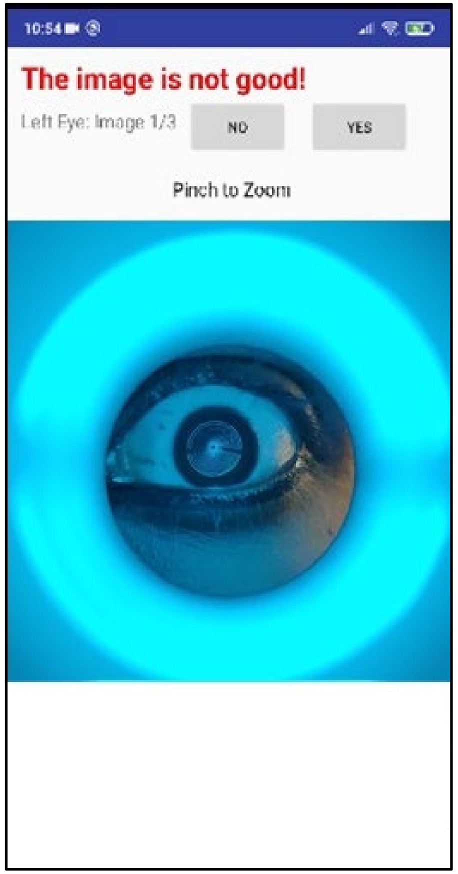
Keratoconus Diagnosis

	Mire Image	Curvature Heatmap
Non-Keratoconus Example		
Keratoconus Example		

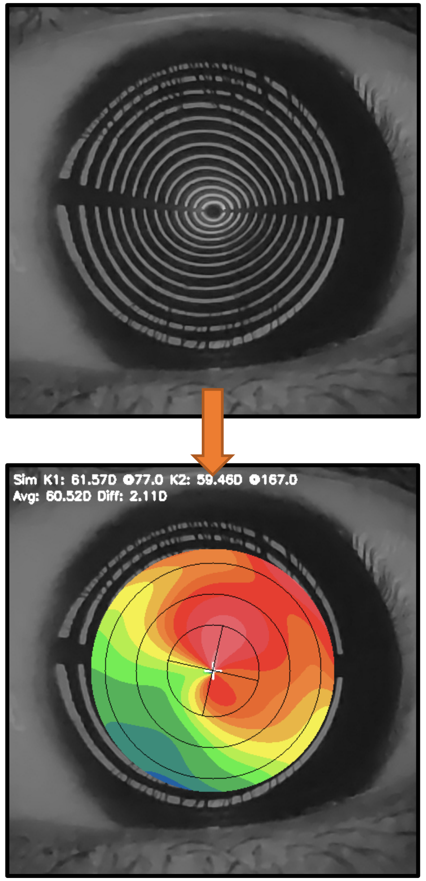
SmartKC: Low-Cost Corneal Topographer

1 Placido Head





2 Intelligent Smartphone App



3 Output

Gairola et al. SmartKC: Smartphone-based Corneal Topographer for Keratoconus Detection. In Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT), V:5, I:4, 2021

SmartKC: Low-Cost Corneal Topographer

In a clinical evaluation on

101 eyes (34 KC, 67 Non-KC)

by 4 ophthalmologists,

SmartKC achieves a

Sensitivity: 92.3 - 94.1%

Specificity: 95.9% - 100.0%

To correctly identify people **with** the disease.

Sensitivity = TP/(TP+FN)

To correctly identify people **without** the disease.

Specificity = TN/(TN+FP)

Need for Automation

Corneal topographers are highly accurate. But …

Output heatmaps need to be evaluated by doctors.

- 1 doctor per 1000 people in the Global South[1]
- Doctors' evaluation suffers from subjectivity
  - Eg: In *SmartKC* evaluation, for 30.7% eyes atleast 1 of 4 doctors' diagnosis did not agree with the rest.
  - This number was 42.6% for Optikon Keratron (medical topographer)

Need for Automation

Requirements

1. An accurate, automated method to detect keratoconus,
2. works for low-cost devices (like *SmartKC*)

Goal: To enable mass screening for keratoconus and prevent blindness.

Related Work

Prior works have demonstrated efficacy of DNNs for keratoconus diagnosis.

Input: Color-coded heatmaps generated from clinical devices based on

- Optical Coherence Tomography
- Schiemflug-imaging
- Placido disc reflection

Output: Diagnosis (keratoconus or no-keratoconus)

Related Work

Prior work was only limited to medical-grade topographers.

Our Focus

Automated method for detecting keratoconus, from topography heatmaps generated by low-cost *SmartKC* device.

Contributions:

- a dual-headed CNN-based keratoconus detection algorithm for *SmartKC,*
- efficient use of limited data by using 2-stage transfer learning and domain specific augmentations,
- evaluation on topography heatmaps from actual patients using *SmartKC* and a medical-grade topographer (*Optikon Keratron).*

Dataset

SmartKC dataset: had only few samples 114 (68 Non-KC, 46 KC)

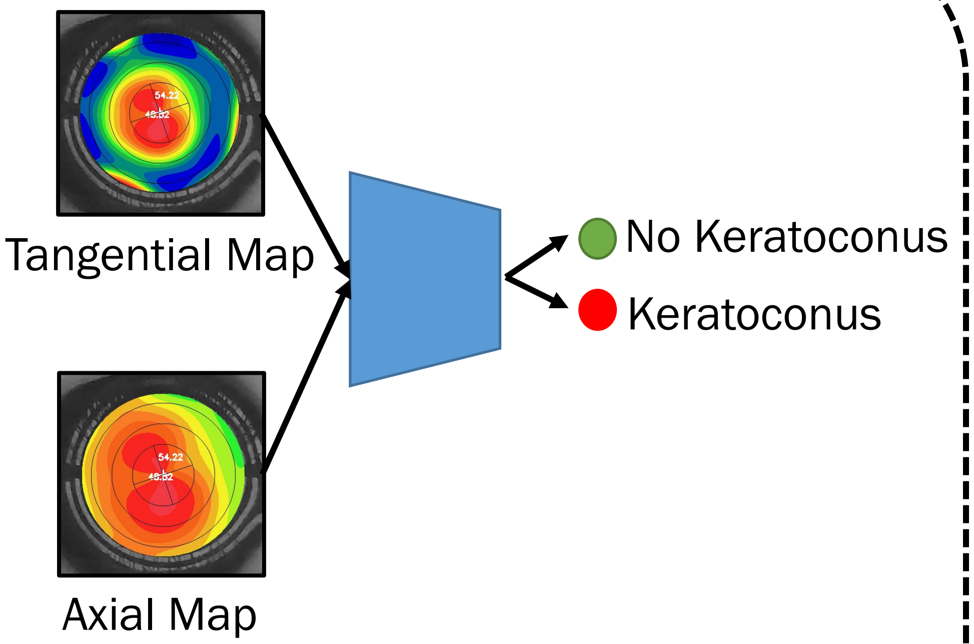
Keratron dataset: retrospective data from Keratron database at hospital

- 2110 samples: 1637 Non-KC, 473 KC

Each sample consisted of:

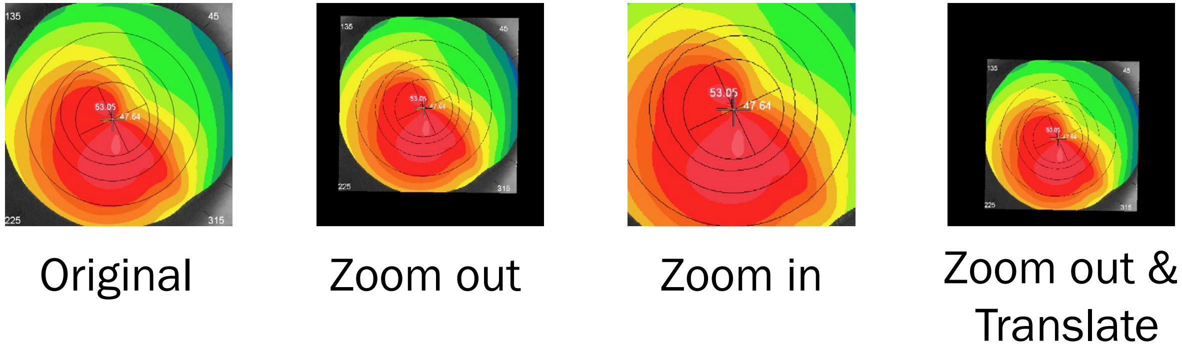
1. Axial heatmap, Tangential heatmap, Mire Image
2. Simulated keratometry values (K1, K2) and PPK (percentage probability of keratoconus)

Proposed Solution: Overview



1. Dual headed CNN

2. Two-stage transfer learning



3. Domain specific augmentations

Proposed Solution: Pre-processing

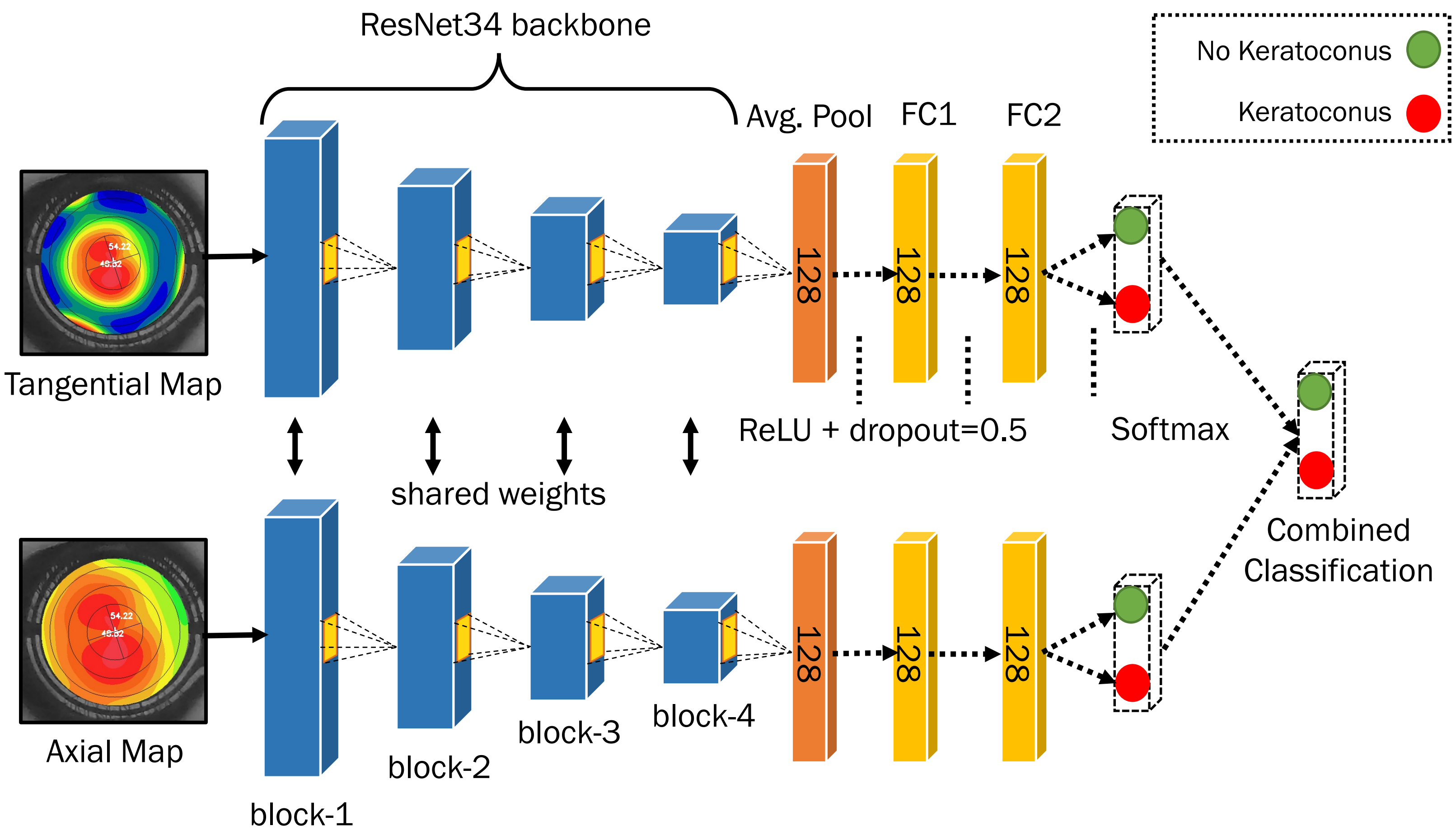
Standardized

- Heatmaps **cropped** and **resized** to fixed shape: 512 x 512

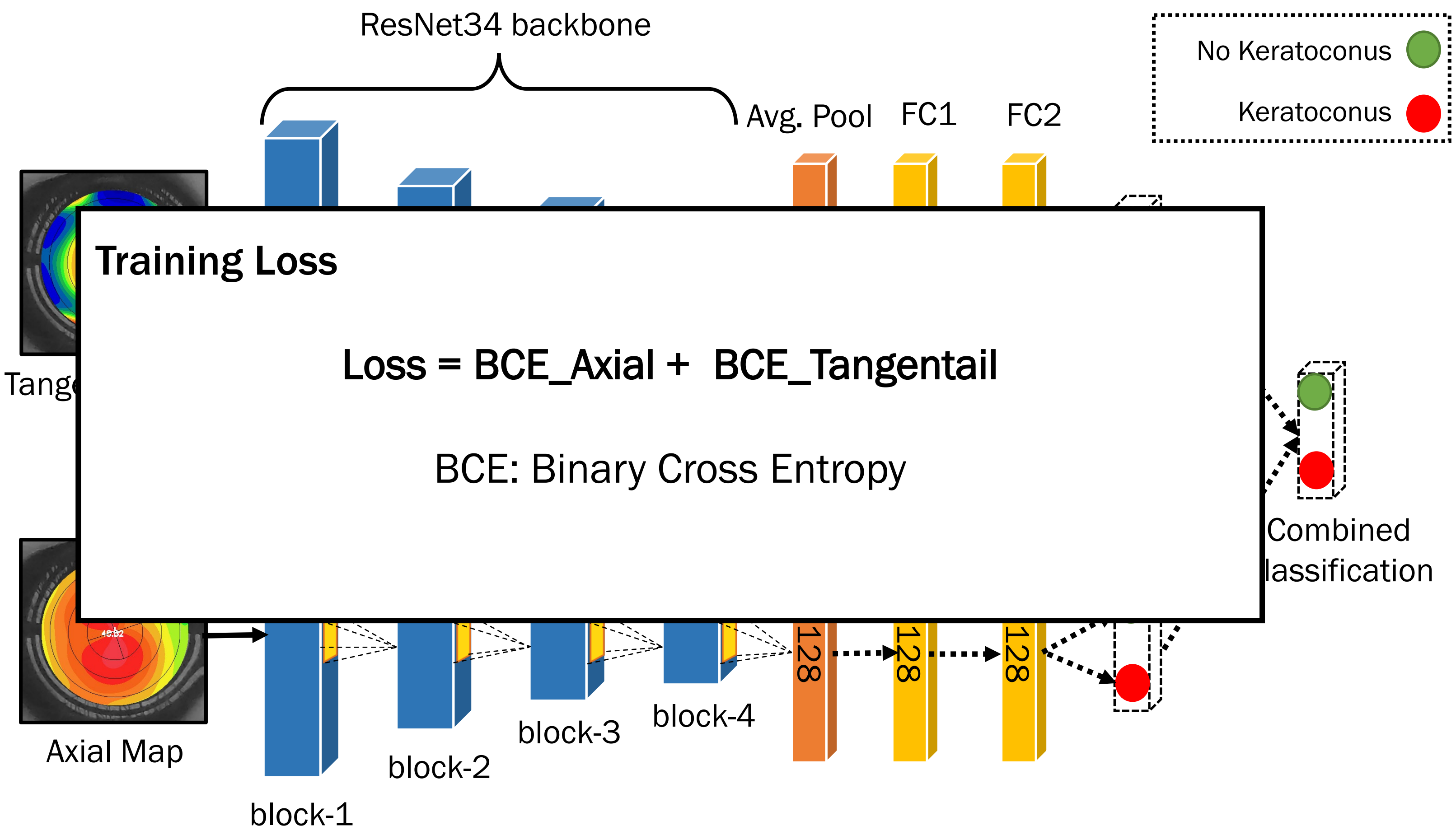
Normalization

- Z-normalization to each channel of RGB image
- $x' = \frac{(x-\mu)}{\sigma}$;
- where μ is dataset mean, σ is dataset standard deviation

Proposed Solution: dual headed CNN



Proposed Solution: dual headed CNN



Training Loss

Loss = BCE_Axial + BCE_Tangentail

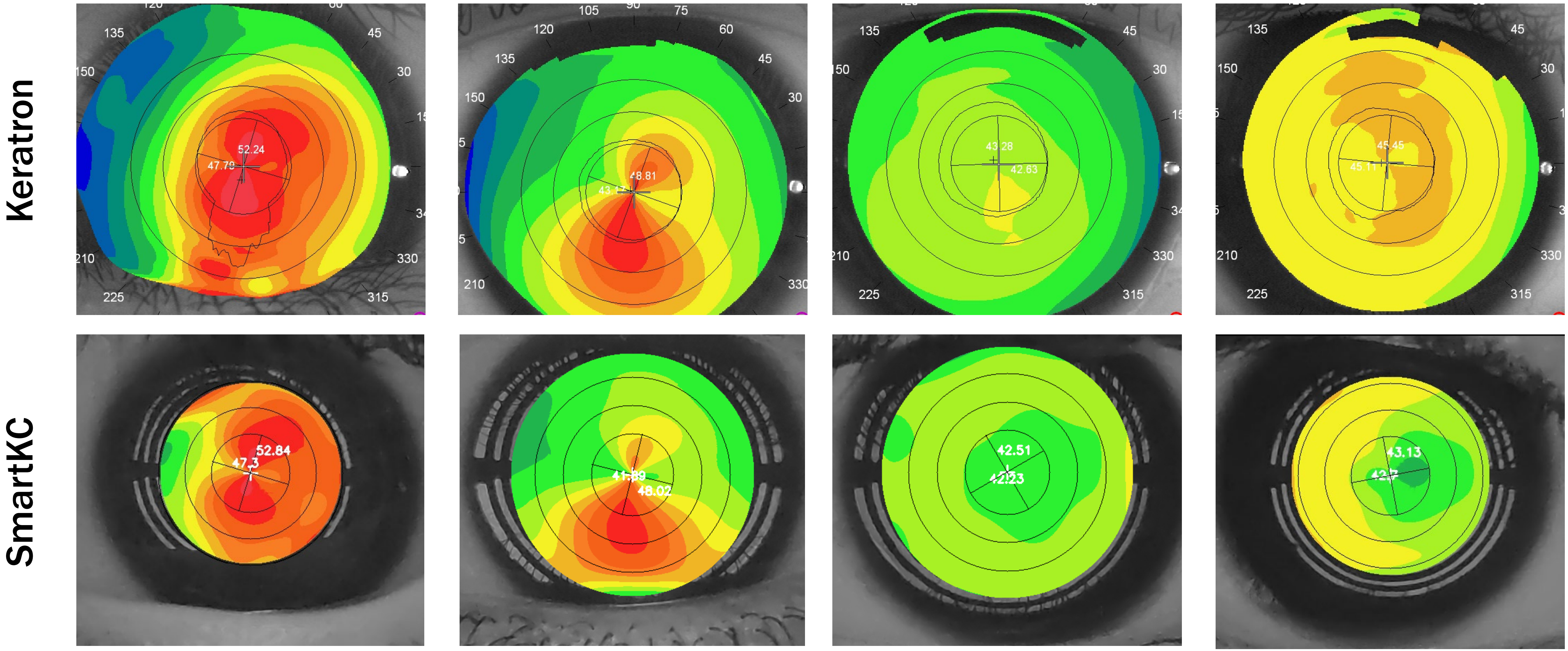
BCE: Binary Cross Entropy

Proposed Solution: 2-stage transfer learning

2-stage transfer learning strategy

- Pretrain model on ImageNet dataset, fine-tune on Keratron dataset (2110 samples)
  - 200 epochs, LR: 1e-3 (fixed)
- Fine-tune on 50% of SmartKC dataset.
  - 100 epochs, LR: 1e-4 (linear decay)

SmartKC vs Keratron (scale, location difference)



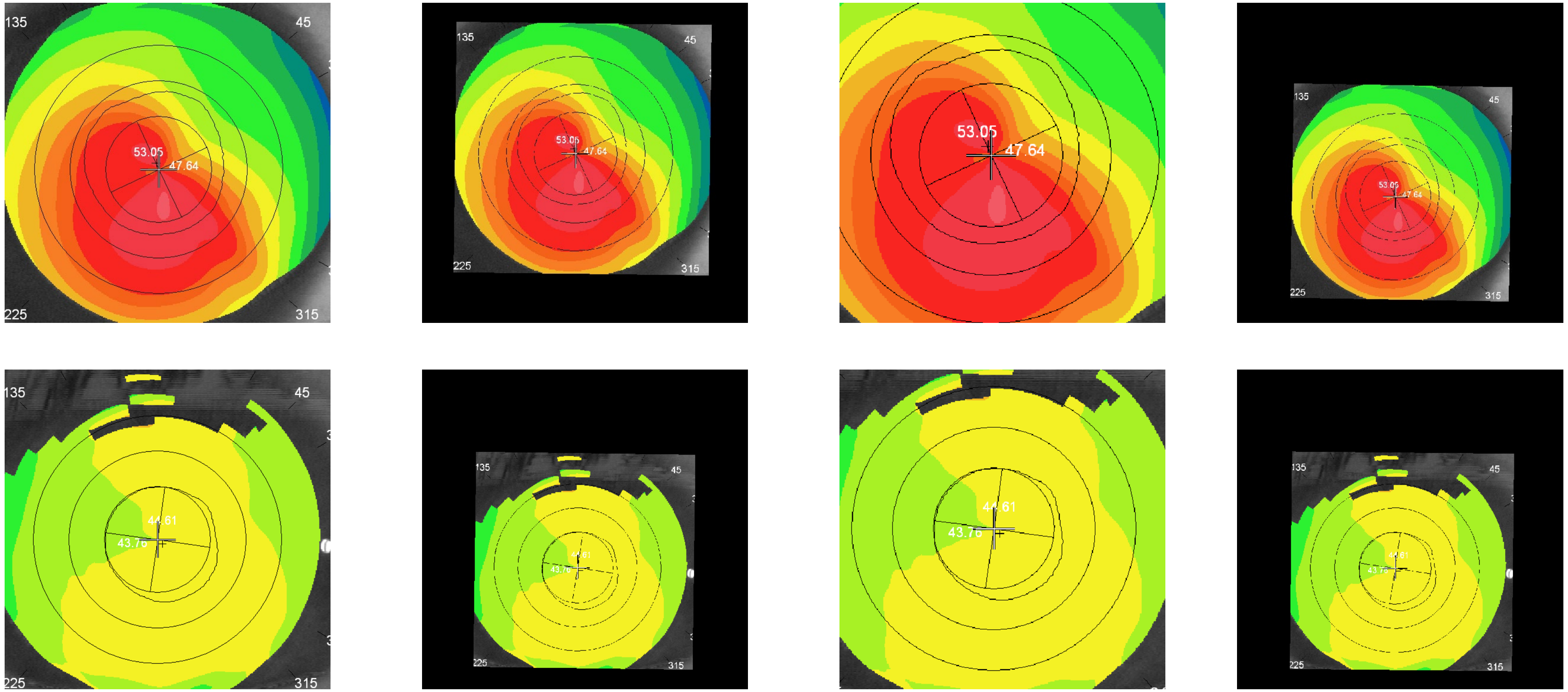
Proposed Solution: augmentations

3

Domain specific augmentations

KC

No-KC



Original | Zoom out | Zoom in | Zoom out & Translate

Proposed Solution: augmentations

Mixup augmentations

Given samples x_i, x_j with labels y_i, $y_{j,}$ new sample (x', y') given by:

$$x' = \lambda x_i + (1-\lambda)x_j$$

$$y' = \lambda y_i + (1-\lambda)y_j$$

where $\lambda \in [0, 1]$

Hongyi Zhang et al. "mixup: Beyond Empirical Risk Minimization". In: ArXiv abs/1710.09412 (2018)

Results

Eval. Data	Model	Se	Sp	Acc
SmartKC-data (57 samples)	SVM	80.4%	100.0%	92.1%
	Dual-head CNN†	65.2%	76.5%	71.9%
	Dual-head CNN*	91.3%	94.2%	93.1%
Keratron-data (114 samples)	PPK	89.4%	94.2%	92.2%
	SVM	78.3%	95.5%	88.6%
	Dual-head CNN‡	94.7%	93.4%	93.9%

Sensitivity (Se) = TP/(TP+FN)

Specificity (Sp) = TN/(TN+FP)

Accuracy (Acc) = (TP+TN)/(TP+FN+TN+FP)

†: fine-tuned only on SmartKC-data.

*: fine-tuned on Keratron-data (stage-1) and 50% of SmartKC-data (stage-2).

‡: fine-tuned only on Keratron-data (stage-1)

What next?

Scaling the SmartKC system for multi-site larger evaluation

Training model on larger dataset

Real-world deployment of SmartKC in Sankara clinics

- With automated diagnosis for mass screening of keratoconus

Thank you ☺