LEVERAGING DEEP LEARNING TO ENHANCE IOL POWER CALCULATIONS

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INTRODUCTION

- Accurate measurement or prediction of total corneal astigmatism (TCA) is crucial for selecting the appropriate power and orientation of toric intraocular lenses (IOLs). Traditionally, emphasis was placed on measuring anterior corneal astigmatism (ACA) from the easily accessible anterior surface. However, posterior corneal astigmatism (PCA) also contributes significantly to TCA, impacting optimal IOL selection.
- Since PCA resides on the less accessible posterior corneal surface, current measurement devices introduce greater variability and noise into their readings.
- Accurate IOL power prediction ensures successful surgical outcomes by minimizing over- or under-corrections, reducing residual refractive errors that cause visual distortions, and ultimately enhancing patient satisfaction. Greater accuracy in TCA prediction translates to more precise estimations of PCA.

METHOD

- A multivariate linear regression neural network was used to train 80% of our large dataset of 19,502 eyes consisting of patients who qualified for refractive surgery.
- RMSE and R^2 were key metrics used to evaluate model performance.

MAGNITUDE: Age, ACA Magnitude, ACA Axis → Neural Network → Predicted TCA Magnitude

AXIS: Age, Predicted TCA Magnitude, TCA Magnitude, ACA Axis → Neural Network → Predicted TCA Axis

Input Layer → Linear Layer → ReLU Activation → Batch Normalization → Linear Layer → Output

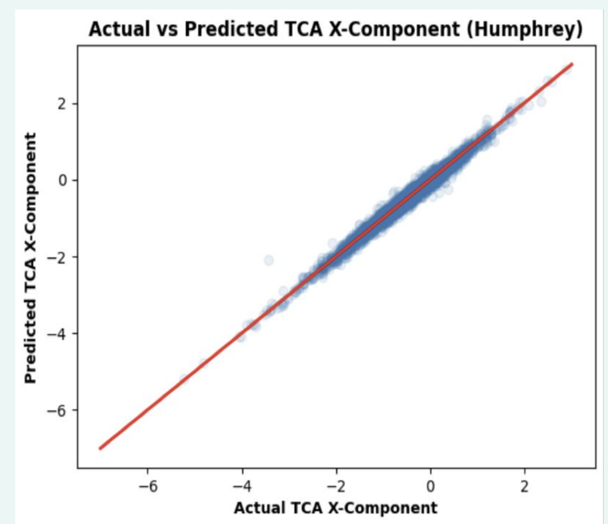
Raw Dataset → Training

Cravy Method → $X = M \times \cos(\theta)$, $Y = M \times \sin(\theta)$ → Training

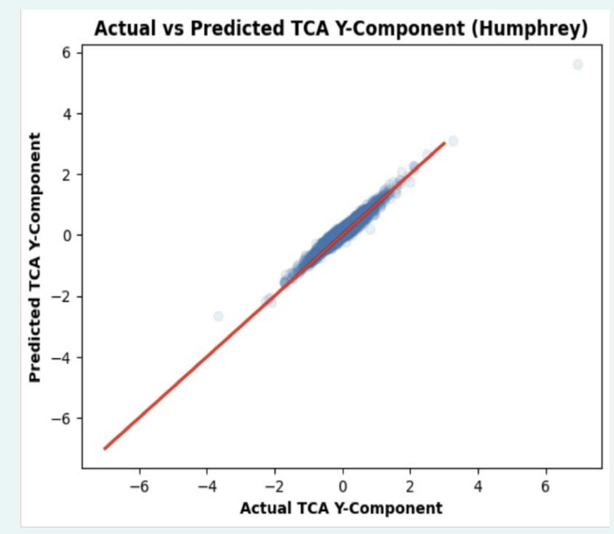
Humphrey Method → $J_0 = C \times \cos(2\theta)$, $J_{45} = C \times \sin(2\theta)$ → Training [1]

RESULTS & DISCUSSION

- The deep learning model utilizing the Humphrey method for vectorizing the ACA into X and Y components achieved the best results.

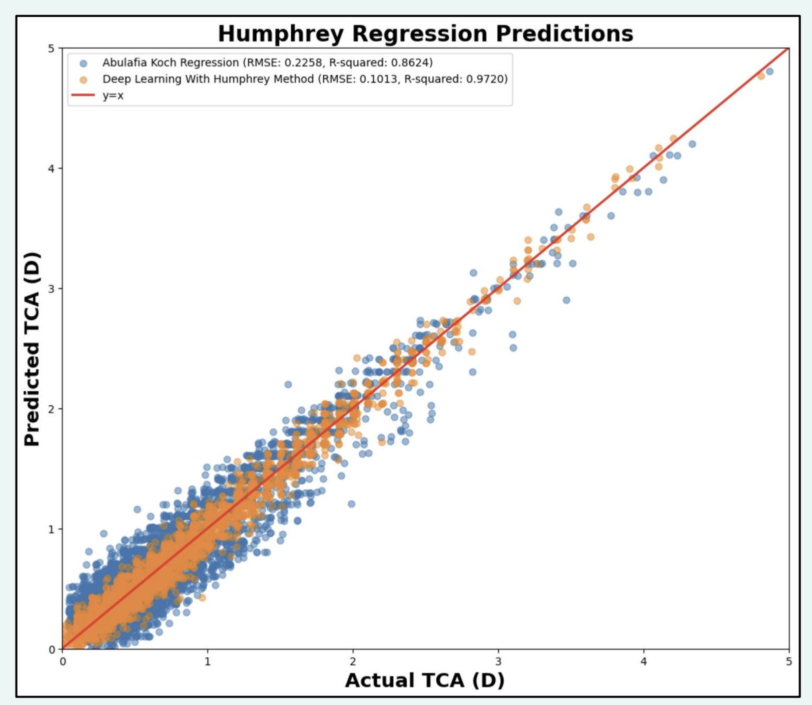


RMSE = 0.0995
R^2 = 0.9832



RMSE = 0.1013
R^2 = 0.9558

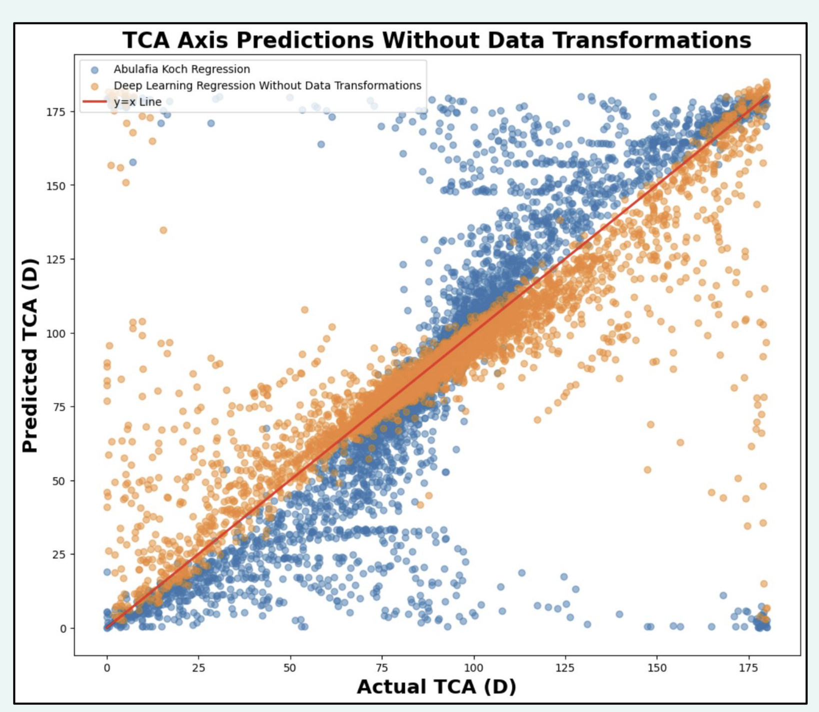
- Reconstructing the TCA from the predicted X and Y components yielded an overall TCA magnitude prediction. There was no significant difference in RMSE between the Humphrey and raw dataset models.

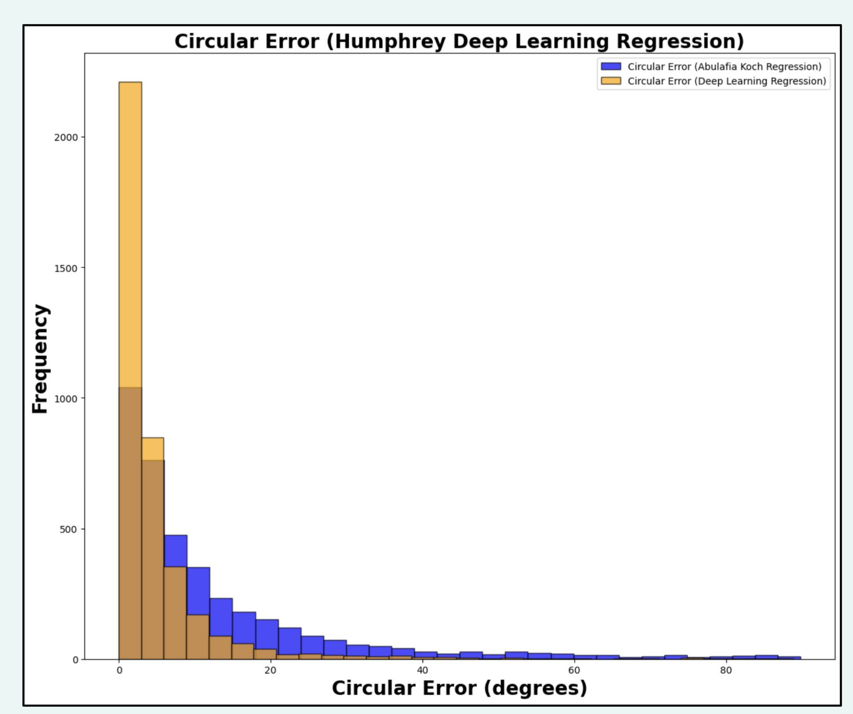


Conventional Method:
RMSE = 0.2258
R-squared = 0.8624

Deep Learning:
RMSE = 0.1013
R-squared = 0.9720

- The predicted axis displayed a significantly more linear trend compared to the Abulafia-Koch model, indicating a substantial reduction in over- and under-prediction. Moreover, the error in axis prediction was considerably lower than both the Abulafia-Koch model and the deep learning model using the raw dataset.

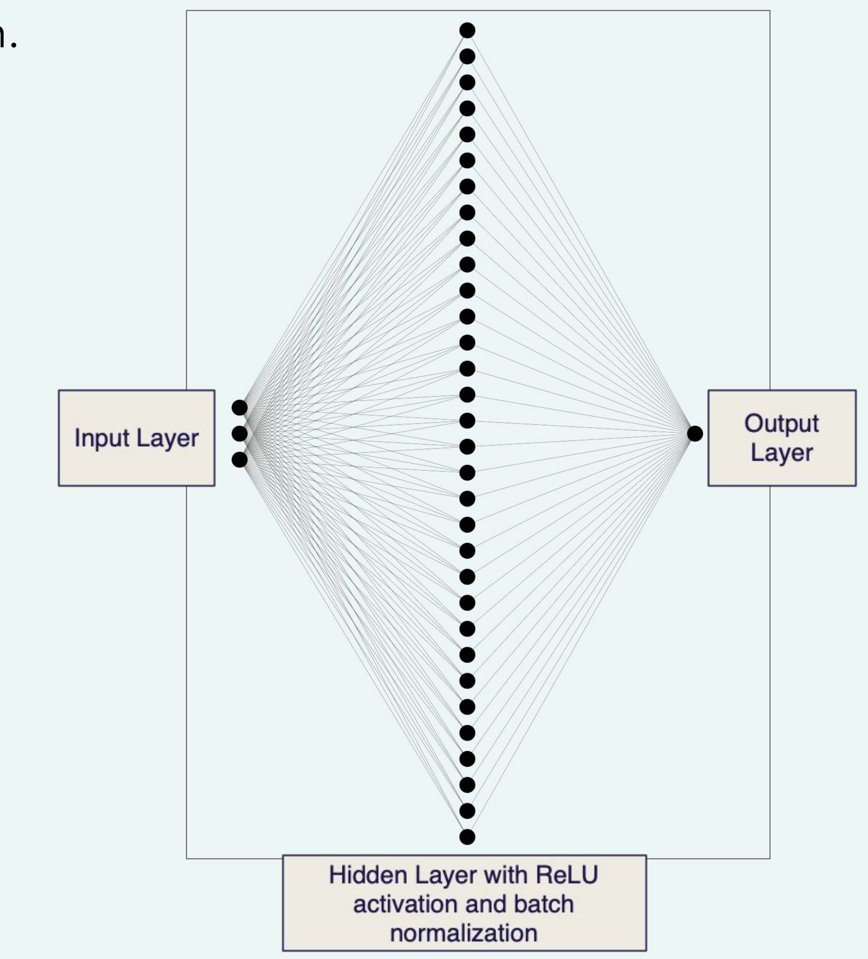




Deep Learning:
Higher frequency of error in the first two bins (0-6 degrees)

CONCLUSION

- Conventional methods of TCA prediction relying on limited datasets and neglecting age as a factor can introduce inaccuracies such as the Kane formula (N=823 eyes) and the Abulafia-Koch formula (N=68 eyes).
- This study demonstrates the potential of deep learning on a massive dataset to overcome these limitations. Our deep learning model predicts TCA with greater accuracy compared to existing formulas.
- Our model has the potential to minimize residual refractive errors and improve post-surgical visual outcomes, ultimately leading to greater patient and surgeon satisfaction.



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1. Morlet, N. (2001). Astigmatism and the analysis of its surgical correction. *British Journal of Ophthalmology*, *85*(9), 1127–1138. https://doi.org/10.1136/bjo.85.9.1127

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