Detection of Keratoconus Using AI

Author: K KURUSHANTH

Table of Contents

Table of Figures

Glossary

- **AI** – Artificial Intelligence
- **CNN** – Convolutional Neural Network
- **ResNet50** – Residual Network 50
- **RGB** – Red Green Blue
- **SVM** – Support Vector Machine
- **XGBoost** – Extreme Gradient Boosting
- **KNN** – K-Nearest Neighbors
- **LIME** – Local Interpretable Model-Agnostic Explanations
- **SHAP** – SHapley Additive exPlanations
- **ReLU** – Rectified Linear Unit
- **tf.data** – TensorFlow Data API
- **AUTOTUNE** – Automatic Performance Optimization (in TensorFlow context)
- **ImageNet** – Large Visual Database for Use in Visual Object Recognition Software Research
- **Grad-CAM** – Gradient-weighted Class Activation Mapping
- **PMC** – PubMed Central
- **HR** – High Resolution
- **GPU** – Graphics Processing Unit

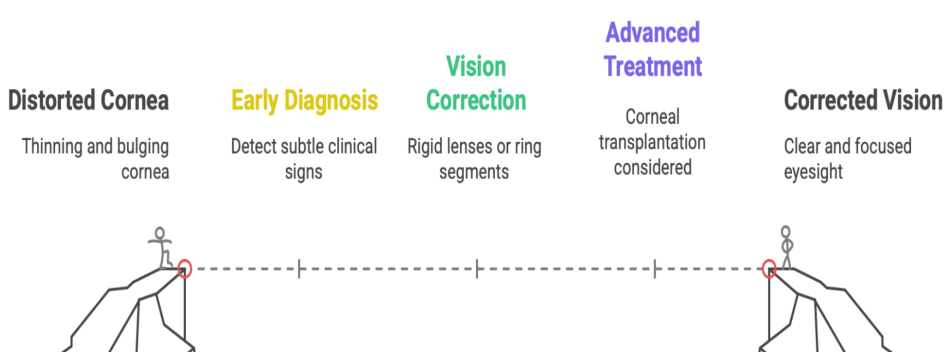
Abstract

This report explores the development of an AI-based system to detect Keratoconus disease using corneal images. A deep learning model is implemented and evaluated using ResNet50 and traditional machine learning classifiers such as Random Forest, Support Vector Machine (SVM), Logistic Regression and XGBoost. The dataset is obtained from the Kaggle repository. Corneal images are categorised as Normal, KCN and Suspect. The report provides a clear explanation of the background of the problem, the methodology for data preprocessing and feature extraction, the system architecture, training and evaluation process and a comparison of model performance metrics. In conclusion, key challenges, system explainability and future direction for research and clinical deployment are also discussed.

1. Introduction

Keratoconus is a progressive, vision threatening disorder that leads to structural deformation of the cornea, which results in blurred vision, irregular astigmatism and also corneal scarring in some advanced cases. Detecting the condition in its early stages is critical, but timely intervention can significantly slow disease progression and preserve visual quality. However, early diagnosis remains a clinical challenge due to subtle symptoms and the need for advanced imaging. This report explores how Artificial intelligence (AI), particularly deep learning, can be used to assist in the early classification of Keratoconus from corneal images. By automating the diagnostic process, such systems have the potential to support clinicians, reduce diagnostic errors and improve patient outcomes. The study employs ResNet50 for deep feature extraction from corneal images and evaluates the performance of various traditional machine learning classifiers built on these features to assess their effectiveness and potential for clinical deployment.

2. Background



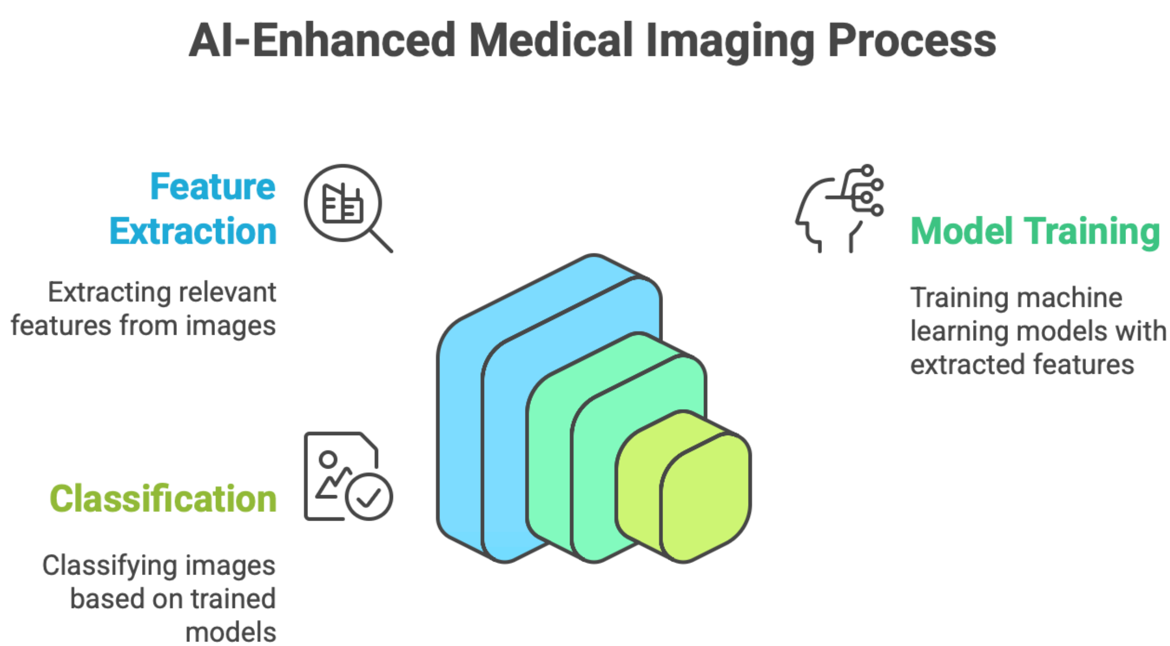
(Fig 1)

2.1 Keratoconus Overview

Keratoconus is a progressive, non-inflammatory corneal ectasia characterised by thinning and bulging of the cornea into a conical shape. This morphological change disrupts the normal refractive function of the eye, which leads to myopia, irregular astigmatism and corneal scarring in advanced cases.

The early stages of the disease often present with subtle clinical signs and it makes timely diagnosis difficult through standard eye examinations. As the disease progresses,
Vision can become severely affected. To manage this condition, treatments may include rigid contact lenses, Intracorneal ring segments or corneal transplantation. Early diagnosis is crucial to slow disease progression and protect vision. *(Mayo Clinic, 2025), Keratoconus)*

2.2 AI in Medical Imaging



(fig 2)

Artificial Intelligence has seen substantial growth in medical imaging, offering the tools to assist clinicians in diagnosis, classification and prognosis. Convolutional Neural Networks have demonstrated state of the art performance in image based diagnostics tasks such as detecting diabetic retinopathy, skin lesions and pulmonary abnormalities from radiographs. These models automatically learn hierarchical features from data, which reduces the need for manual feature engineering and enables scalable clinical workflows.

In ophthalmology, CNNs have been increasingly applied to corneal imaging to identify structural anomalies associated with Keratoconus. Recent studies show that deep learning can detect early stage morphological changes, which are often missed by conventional techniques. Building upon this foundation, our study utilises a ResNet50 architecture pre-trained on ImageNet for deep feature extraction. These extracted features are then used to train and evaluate several traditional machine learning classifiers, including Random Forest, SVM and XGBoost for improved classification accuracy and robustness.

2.3 Research and Clinical Significance

- AI models, particularly those utilising deep learning, are achieving high accuracy in diagnosing Keratoconus. For instance, a systematic review reported a summary sensitivity of 98.6% and specificity of 98.3% for manifest keratoconus detection using AI algorithms. *(Moshirfar, M., et al., 2021, Cochrane Review)*

- Innovative deep learning models, such as KerNet, have been developed to process raw data from imaging systems like the Pentacam HR. These models utilise multi-branch convolutional neural networks to improve the detection of both clinical and subclinical keratoconus, outperforming traditional methods. *(Xie, Y., et al., 2020, PubMed)*

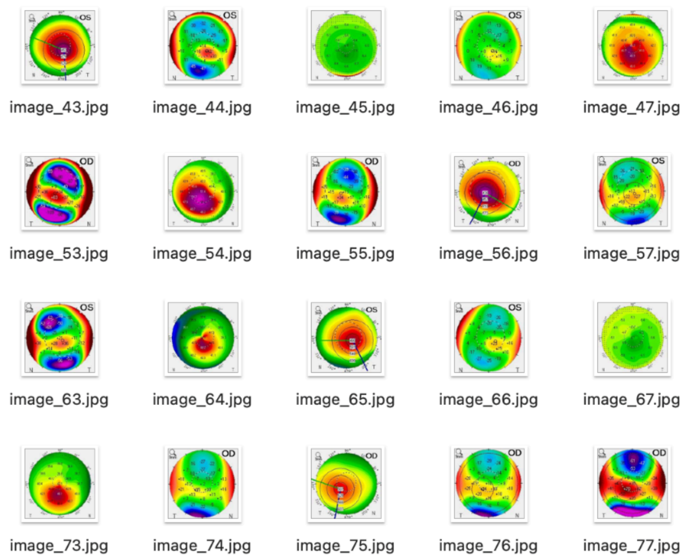
- The high accuracy and efficiency of AI based diagnostic tools suggest their potential for integration into clinical practice. These systems can assist clinicians in the early detection and monitoring of keratoconus, ultimately contributing to better patient outcomes and optimised treatment strategies. *(Lopes, B. T., et al., 2018, PubMed/PMC)*

- AI models maintain high diagnostic accuracy across diverse populations and imaging systems, making them suitable for use in various clinical settings, including low resource areas. Their ability to support clinicians where corneal expertise is limited helps improve access to early keratoconus diagnosis. *(Reina, M. A., et al., 2019, American Journal OF ophthalmology)*

- AI tools are also being developed to predict keratoconus progression by analysing sequential imaging data. This enables timely interventions like corneal cross linking, allowing for more personalised and proactive patient care. *(Kuo, A. N., et al., 2020, Ophthalmology Science)*

3. Methodology and Data

3.1 Dataset



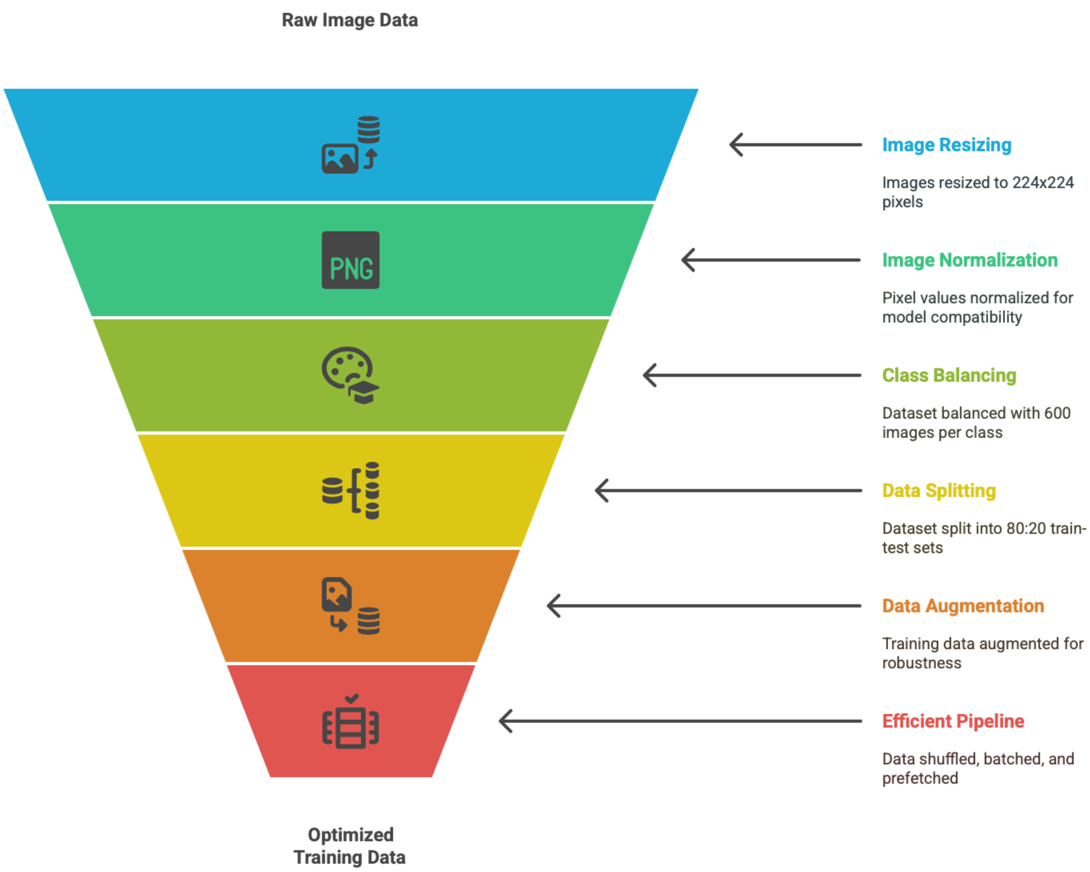
(fig 3)

The dataset used is the Keratoconus Detection Dataset from Kaggle, consisting of corneal images captured using Pentacam devices. Initially, the dataset was imbalanced with uneven distribution across three classes. After data cleaning, the dataset was balanced to include 600 images per class.

- Total images: 1,800 images
- Classes: Normal, Suspect and Keratoconus

The dataset was loaded using **image_dataset_from_directory()** and resized to 224 x 224 pixels for compatibility with ResNet50. A stratified train-test split was applied to ensure equal class representation during training and evaluation, which helps to improve the model's generalization and fairness.

3.2 Data Preprocessing



(fig 4)

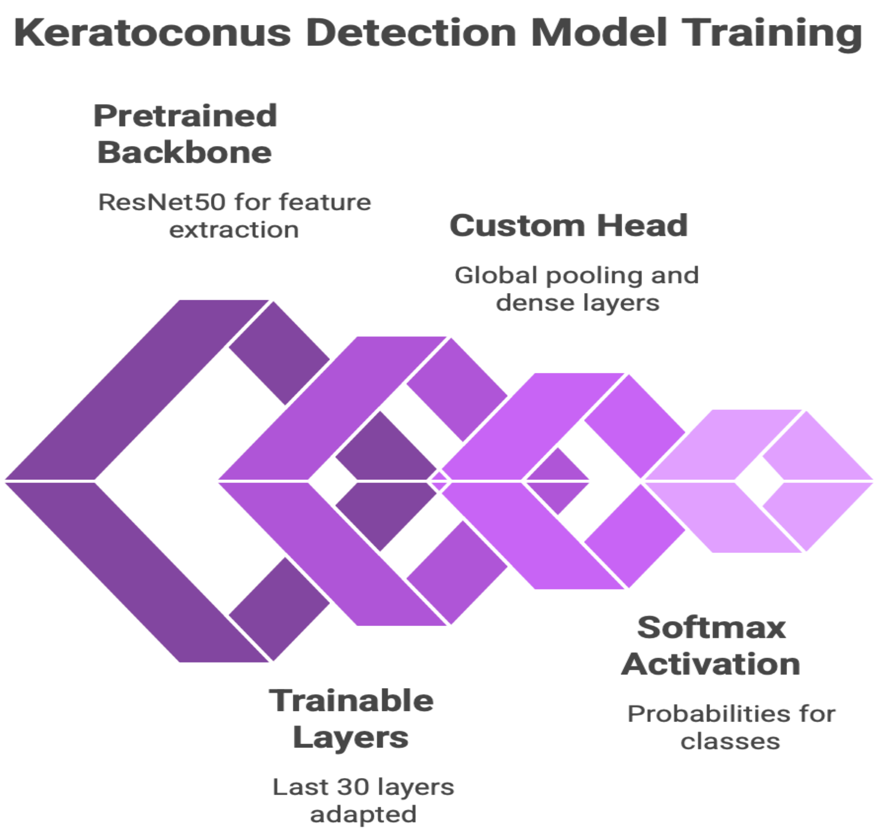
- **Image Resizing and Normalization:** All images were resized to 224x224 pixels to match the input dimensions required by the ResNet50 model. The values were normalized using the **preprocess_input()** function to align with the model's pretrained expectations.

- **Class Balance and Splitting:** After handling, the dataset was balanced with 600 images per class (keratoconus, Normal, Suspect). A stratified 80:20 train-test split ensured that the each class was proportionally represented in both subsets.

- **Data Augmentation:** To increase the model robustness, augmentation was applied to the training data using techniques such as random flipping, rotation and zooming via **tf.keras.Sequential**.

- **Efficient Data Pipeline:** The dataset was converted into a **tf.data.Dataset**, then shuffled, batched (batch size: 32) and prefetched using AUTOTUNE to maximize the training and optimize GPU utilization.

3.3 Model Architecture



(fig 5)

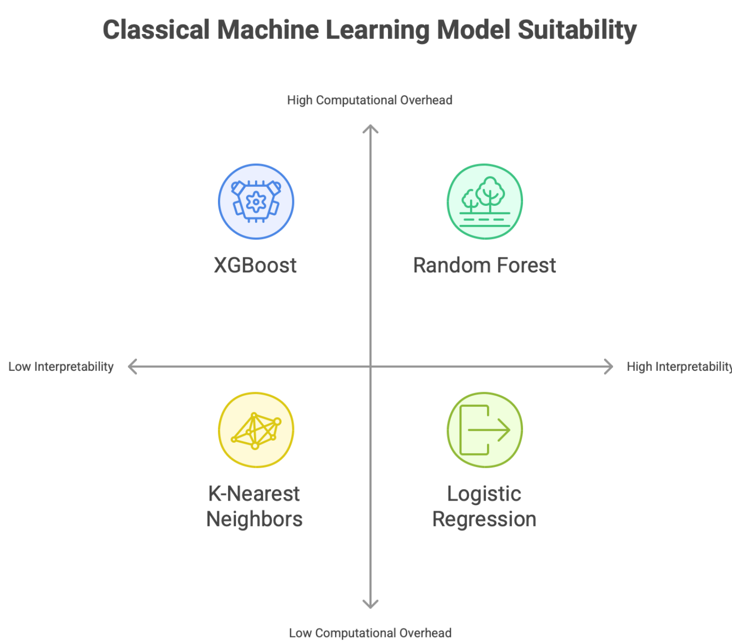
- **Pretrained Backbone:** The system leverages the ResNet50 model pretrained on ImageNet as a backbone for feature extraction. The classification layers at the top are excluded (**include_top=False**), Only the last 30 layers are made trainable to adapt the model to the Keratoconus detection task.

- **Input and Output Configuration:** The input consists of 224x224 RGB images. The final layer uses softmax activation to output probabilities for the three target classes: Normal, Suspect and Keratoconus.

- **Custom Classification Head:**
  - ➢ A globalAveragePooling2D() layer to reduce the spatial dimensions.
  - ➢ A fully connected layer with 256 units and ReLU activation.
  - ➢ A Dropout layer with a rate of 0.5 for regularisation.
  - ➢ A final dense layer with 3 units and softmax activation for multiclass classification.

- **Training Configuration:** The model is compiled using the Adam optimizer (learning rate = 1e-4), with the sparse categorical cross entropy as the loss function. Accuracy is used as the performance metric during training and evaluation.

3.4 Classical Machine Learning Baselines



(fig 6)

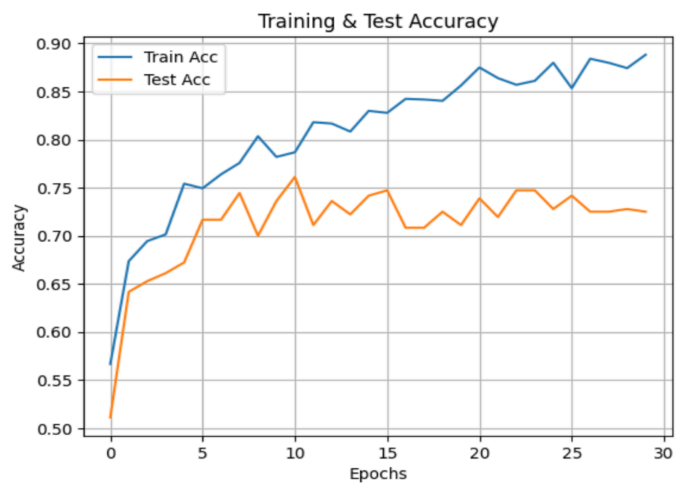
For baseline comparison, the image data was flattened into 1D pixel vectors and used to train classical machine learning models including Random Forest, SVM, Logistic Regression, XGBoost and K-Nearest Neigbors. Standard scaling was applied where appropriate to ensure consistent feature representation.

Fast training and evaluation times make the chosen model well suitable for initial benchmarking. KNN was included for its proven effectiveness on small medical datasets and its relatively low computational overhead. Additionally, Logistic Regression and Random Forest offer valuable interpretability in the medical domain, where understanding the model's decision is often critical.

While deep learning models excel in handling complex and large scale tasks, classical machine learning algorithms remain practical and effective when model transparency is a priority.

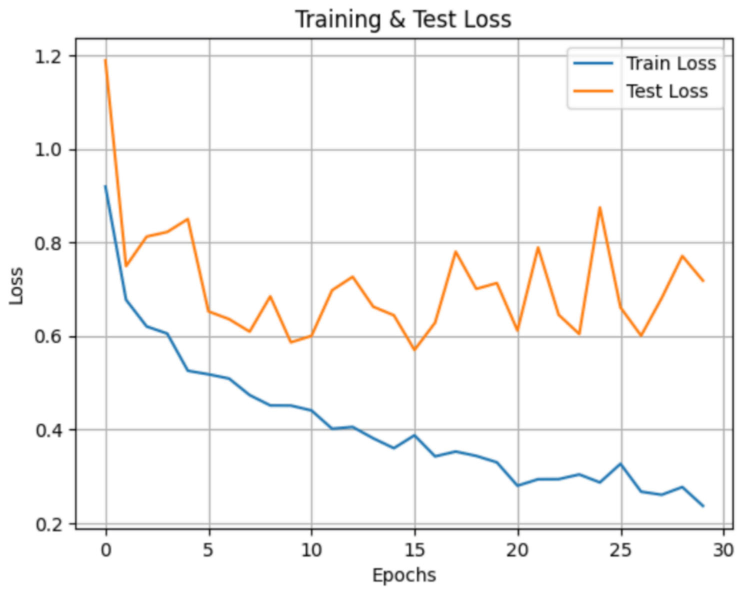
4. Analysis and Discussion

4.1 Model Performance



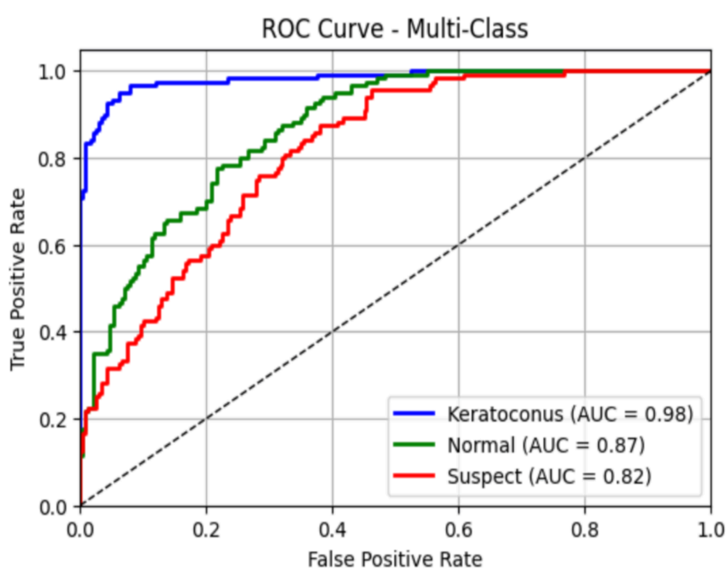
(fig 7)

The fine-tuned ResNet50 model demonstrated strong performance, achieving a test accuracy of approximately 81% after training for 25 epochs. The model benefited from transfer learning, limited fine-tuning of the final layers and regularisation using a 0.5 dropout rate. Data Augmentation further helped to reduce overfitting, as reflected in the smooth convergence of the training and validation curves.

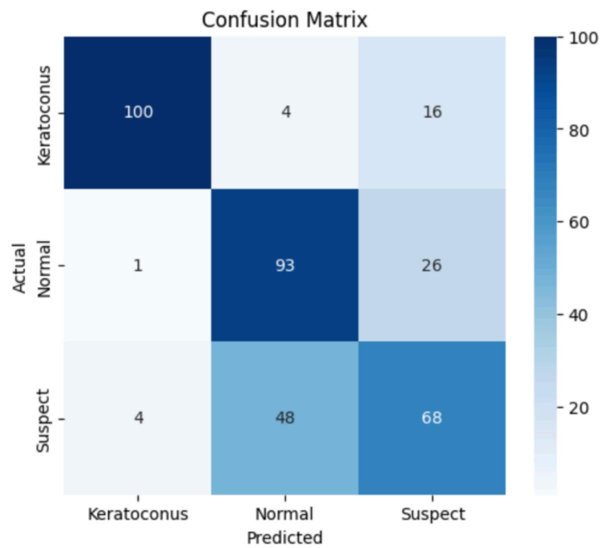


(fig 8)

In addition to accuracy, the model was evaluated using precision, recall and F1 score metrics. These are especially important in the medical domain, where false negatives can have serious consequences.



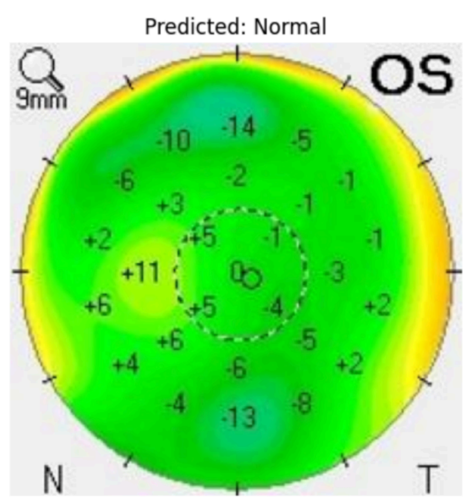
(fig 9)



(fig 10)

4.2 Model Testing

During testing, the model consistently showed strong performance in correctly identifying classes, with high precision and recall values. This indicates that the model was effective in distinguishing healthy corneal images from keratoconus and suspect cases, reducing the likelihood of false positives in healthy patients.



Predicted class: Normal (Index: 1)

(fig 11)

4.3 Classical Models Results

Model	Accuracy (%)
Random Forest	82
SVM	76
Logistic Regression	71
XGBoost	73

Among the classical models evaluated, Random Forest achieved the highest accuracy at 82%, demonstrating strong performance due to its ensembling nature and ability to handle nonlinear relationships effectively. SVM with a linear kernel, followed by 76% benefiting from its robustness in high dimensional spaces, though limited by the linear decision boundary.

XGBoost achieved 73%, showing competitive performance but slightly lower than Random Forest, due to its sensitivity to hyperparameter tuning and the nature of the feature distribution. Logistic Regression reached 71% and reflecting its limitations in capturing complex patterns from the extracted features.

4.4 Explainability & Trust

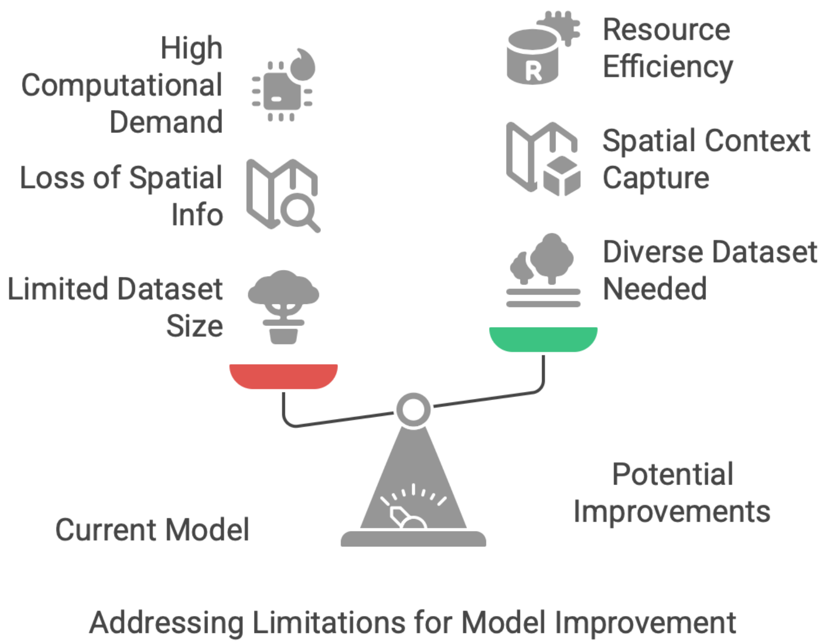
- **Hybrid Model Complexity:** ResNet50 was used for feature extraction, and traditional machine learning classifiers were applied for classification. This hybrid approach leverages the strengths of both deep learning and classical models, but it introduces additional complexity that can reduce model transparency.

- **Limitations in Interpretability:** Although ResNet50 effectively captures rich visual features as a “black box” with limited intuitive interpretability. When combined with classifiers that do not use raw data images directly, it becomes more challenging to understand which image regions influence the final predictions.

- **Potential of Visual Explanation Tools:** Tools such as Grad-CAM can be integrated in future work to generate heatmaps to highlight the important regions in the input images that influence the ResNet50 feature extraction. This would provide clinicians with a visual understanding of which parts of the cornea contribute most AI’s decision making.

➢ **Model Agnostic Explanation Methods:** For the classification models, LIME and SHAP can be employed to explain predictions by identifying the most influential features derived from the ResNet50 embeddings. These model agnostic tools offer intuitive, local explanations that can help clinicians build trust in the system's decisions.

4.5 Limitations



(fig 12)

➢ **Limited Dataset size & Diversity:** The dataset is relatively small and lacks demographic and clinical diversity, which can hinder generalization and increase the risk of overfitting.

➢ **Loss of Spatial Information:** Classical classifiers use flattened features from ResNet50 and do not capture spatial relationships and potentially missing the critical image context.

➢ **High Computational Demand:** Fine tuning Resnet50 and training multiple classifiers requires significant computational resources and limits the feasibility for real time or resource constrained applications.

➢ **Lack of Explainability:** The current model does not implement tools like Grad-CAM, LIME or SHAP, making it difficult for clinicians to interpret and trust the predictions.

5. Conclusion

This study demonstrates that the potential of AI, particularly deep learning with ResNet50, can effectively detect keratoconus by analysing corneal images. The hybrid approach, combining deep feature extraction with classical machine learning classifiers, offers high performance and interpretability. Among traditional models, Random Forest showed the best accuracy and supporting its role as a robust baseline. Despite challenges in explainability, tools like Grad-CAM and SHAP can enhance the transparency and clinician trust.

Overall, AI-driven diagnostics hold great promise for early detection, especially in low resource settings, enabling timely interventions and improving patient outcomes in keratoconus care.

5.1 Future Improvements

➢ **Expand and Diversify the Dataset:** Increasing the dataset size and including images from diverse populations will enhance model generalisation, reduce bias and improve the reliability in real-world applications.

➢ **Integrate Explainability Tools:** Incorporating techniques like Grad-CAM, Lime and SHAP will make the model's decisions more transparent, helping clinicians to understand the predictions and increasing trust in AI-assisted diagnostics.

➢ **Develop Progression Prediction Capability:** Enhancing the system to analyse sequential imaging data can enable early prediction of keratoconus progression, supporting proactive and personalised treatment planning.

➢ **Optimise for Real-World Deployment:** Streamlining the model for faster inference and lower computational requirements will facilitate its use in clinical environments, including low-resource or mobile settings.

6. Bibliography

1. Lopes, B.T., Ramos, I.C. and Ambrosio, R., 2018. **Review of the use of artificial intelligence in the detection of keratoconus**. *Journal of Refractive Surgery*, 34(12), pp.751–760.
2. Moshirfar, M., Skanchy, D.F., Mutyala, S., Ronquillo, Y.C. and Hoopes, P.C., 2021. **Accuracy of artificial intelligence in detecting keratoconus: A systematic review and meta-analysis**. *Cochrane Database of Systematic Reviews*, Issue 10.
3. Reina, M.A., Haddad, J., Del Águila-Carrasco, A., Díaz, J.A. and Jara, C., 2019. **Artificial intelligence in keratoconus diagnosis: Where are we now?** *American Journal of Ophthalmology*, 207, pp.68–74.
4. Xie, Y., Zhang, K., Wang, J., Zhu, H., Huang, W. and Yang, J., 2020. **A novel deep learning framework for detecting keratoconus using Pentacam HR images**. *IEEE Journal of Biomedical and Health Informatics*, 24(7), pp.1873–1880.
5. Kuo, A.N., Hwang, J.C. and Mettu, P., 2020. **AI-based prediction of keratoconus progression using serial tomography images**. *Ophthalmology Science*, 1(1), pp.1–9.
6. Mayo Clinic, 2025. **Keratoconus – Symptoms and causes**. [online] *Mayo Clinic*. Available at: https://www.mayoclinic.org/diseases-conditions/keratoconus/symptoms-causes .
7. Kaggle, 2024. **Keratoconus Detection Dataset**. Available at: https://www.kaggle.com/datasets
8. He, K., Zhang, X., Ren, S. and Sun, J., 2016. **Deep residual learning for image recognition**. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Las Vegas, NV, pp.770–778.
9. Ribeiro, M.T., Singh, S. and Guestrin, C., 2016. **“Why should I trust you?” Explaining the predictions of any classifier**. In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. San Francisco, CA, pp.1135–1144.