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Comparison of Various Deep Learning Models Used to Detect and Classify Keratoconus Disease

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Abstract: ***The corneal condition keratoconus results in both corneal thinning and bulging, along with symptoms like astigmatism, light sensitivity, blurred vision, etc. Your eyes can be affected by genetic, environmental, and age-related problems because they are one of the most complex organs in the human body. From little discomfort to more serious vision problems that could harm your eyesight, this can happen. The screening for keratoconus requires a thorough examination of the cornea using various methods, including slit lamp analysis and corneal tomography. The goal of this study is to identify and categorise keratoconus using various machine-learning methods.***

Keywords: Keratoconus Disease, InceptionV3 Xception, Mobile Net, Deep learning.

I. INTRODUCTION

Approximately one person in every 1,000 develops keratoconus. Indeed, more are likely to contract the infection as we develop better screening techniques. The cornea, the clear lens at the front of the eye, cracking, is what causes keratoconus (like the crystal on a watch). [1], [2][15]. The cornea then abruptly changes from its flat, dome-like shape to one that is more conical and irregular in shape. The cornea's ability to produce a clear image in the eye is deteriorating as a result of this transformation. In actuality, the irregularities in corneal optics and optical disturbances are worsening over time. The primary goal of the model is to identify the earliest manifestations of keratoconus in humans through various scans and feed that information into the system, which will act as a database for the model, enabling it to determine whether a patient has keratoconus and, if so, the severity of the disease they are carrying. The precise cause of keratoconus is uncertain. It can have a genetic or hereditary component [3][4].

In many instances, the disease has no family relatives. Similarly, the majority of children of keratoconus (KC) sufferers do not have the condition. Still, they should be screened for it during the early adolescent years, as early intervention can prevent the condition from worsening over time.

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Thinning of the cornea and biomechanical instability are characteristics of keratoconus [4]. This might be attributable to deviations from the typical collagen structure of the cornea. The cornea's main structural component is collagen [5] [6].

Typically, collagen is a reasonably hefty molecule. For instance, as shown in Fig. 1, it plays a significant role in the formation of bones, muscles, tendons, and ligaments. Keratoconus begins as a result of the corneal structure's fragility and progresses through time. Keratoconus is classified into four disease phases: early keratoconus, moderate keratoconus, advanced keratoconus, and severe keratoconus. This study's objective is to employ deep learning and machine learning to categorise patients with KC precisely [7].

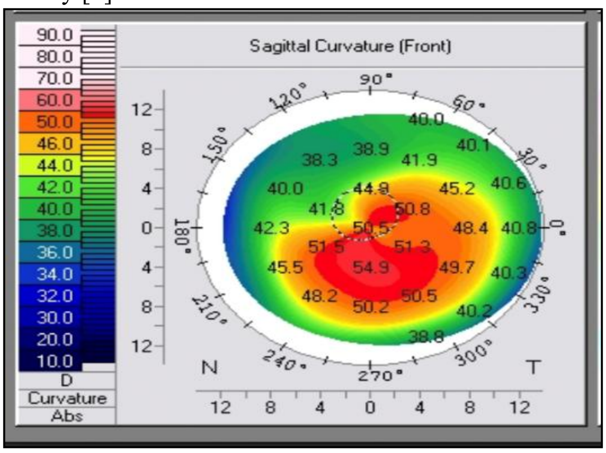

Fig. 1: Keratoconus Affected Cornea of a Sample

In this study, a CNN developed using transfer learning is shown to be capable of identifying keratoconus disease. Medical data is used to validate the detection algorithm. Medical data have been used to train and evaluate deep learning models like InceptionV3, Xception, MobileNet, DenseNet121, DenseNet169, and DenseNet201. With a training accuracy of 94.5% and a validation accuracy of 94.23%, the InceptionV3 model performs best. MobileNet is the model that performs the poorest, with training and validation accuracy of 76% and 75%, respectively [8].

II. MOTIVATION

Your eyes, one of the most intricate organs in the body, are susceptible to inherited, environmental, and ageing-related problems. From little annoyances to more serious visual issues that could harm your eyesight, this can happen. A thorough corneal examination using various techniques is required for the early detection of keratoconus (Screening) and therapy. Include corneal tomography and the investigation of slip lights.

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The project's motivation is to utilise machine learning to identify eye conditions, such as keratoconus.
Early diagnosis of the condition will help patients avoid procedures like corneal transplant surgery, which is only performed in cases of advanced keratoconus. Artificial intelligence (AI) is unquestionably a technique that enables programs to learn and evolve organically without explicit programming. AI is focused on the development of computer frameworks that can display information and utilise it to think for themselves. The most well-known methods for evaluating anterior and posterior corneal surfaces, as well as the overall corneal pachymetry, are corneal topography, corneal tomography, and slip lamp evaluation [9]. These methods are used for early identification (screening) and treatment of keratoconus.

The primary driving force behind this research is to apply machine learning algorithms to aid mankind in combating a condition that has the potential to leave people permanently blind.

III. RELATED WORK

Software may enable producers to develop their equipment to assist experts and enhance the identification process of Keratoconus, either automatically or through specialists. Keratoconus is an eye disease that requires expert care and precise topographical eye-image analysis. This paper deals with the development of a Device for Artificial Intelligence Diagnosis of Keratoconus. This approach would help producers improve them. Apparatus programs to assist specialists in their growth. Their Artificial Intelligence algorithm utilizes features from eye map topography to locate Keratoconus. These characteristics are collected by Pentacam and extracted from topographical photographs of the eye using image processing techniques. [10].
Map (0.976) that discriminates between standard and keratoconic heads. Such deep learning has also shown a precision of 0.874 when classifying the level of the disease. The later curvature chart (0.869) displayed better accuracy, followed by a chart of corneal pachymetry (0.845), anterior curvature map (0.836), gross refractive force map (0.836), corresponding elevation map (0.829) and anterior elevation map (0.820), in stage grouping. [11].
Alexandru Lavric and Popa Valentin proposed the creation of a screening method based on a learning algorithm that automatically detects keratoconus disease using corneal topographies. In the tool that conducts topography as an add-on, the algorithm may be introduced to support the ophthalmologist with 99.3% precision in the quick screening of their patients. The Kerato Detect algorithm analyses the eye's corneal topography using a coevolutionary neural network (CNN), capable of extracting and learning the characteristics of a keratoconus eye. Kerato Detect will enable the ophthalmologist to screen their patients rapidly, thereby reducing diagnostic errors and promoting effective treatment. [12].
It claimed that the early stages of keratoconus are challenging to diagnose and that better outcomes can be achieved by using the height decentration index and the vertical asymmetry index. Twenty-seven individuals afflicted with unilateral keratoconus were followed up to assess initial markers of progress against the keratoconus condition, which had not yet demonstrated any ectatic improvements in their fellow eyes. Variables were associated with 50 normal eyes with no known illness. The D-index is best adapted to detect an ectasia as the condition progresses. Astigmatism, keratometry and pachymetry barely alter in the early stages, and these values are less appropriate for early detection than corneal elevation parameters of 93 per cent accuracy [13]
Provided that the keratoconus status and severity can now be well-defined using automated, unmonitored clustering algorithms that utilise topographic, tomographic, and corneal thickness profiles. We developed an unmonitored machine learning algorithm and applied it to broad corneal parameters to classify and track phases of keratoconus. Multiple centres throughout Japan have compiled a comprehensive dataset of swept-source optical coherence tomography (OCT) images of 12,242 eyes, acquired using CASIA OCT Imaging Systems SS-1000. A total of 3,156 eyes were selected with an Ectasia Status Index (ESI) ranging from 0 to 100%. Four hundred and twenty corneal topography, height, and pachymetry parameters (excluding the ESI Keratoconus indices) were identified. [14] The algorithm encompassed three essential measures. 1) Principal component analysis (PCA) was used to linearly reduce the input data dimensionality from 420 to eight key components. 2) Manifold learning was then applied to reduce further the selected main components to two nonlinear parameters. 3) Throughout the results, density-based clustering was extended to its parameters to identify eyes with keratoconus. Visualisation of clusters in 2D space was used to assess learning efficiency subjectively, and ESI was used to determine the precision of the defined clusters. In corneal clinics and laboratory settings, this technique will be used to help diagnose, track improvements and growth and enhance our knowledge of corneal shifts in keratoconus. The precision in recognizing safe eyes is 94.1 per cent, and 97.7 per cent in defining the eye with keratoconus [15].

IV. METHODOLOGY

In Fig. 2, the process is a generalised one that is used on various architectures for comparative analysis.

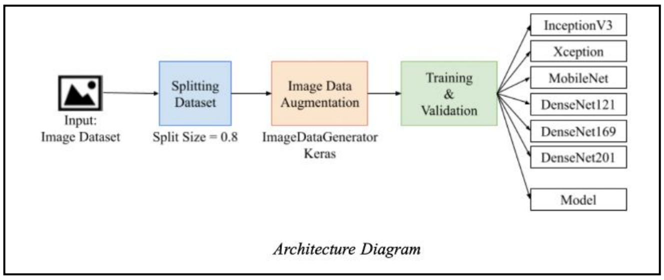

Fig. 2: Methodology of the solution

To make the approach of this project easier to understand, it has been broken down into the following steps: dataset preparation, image data augmentation, training, and validation.

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The most common method for identifying and confirming keratoconus is to create a corneal topography, which an expert ophthalmologist then analyses. These pictures will serve as the input for our system. The dataset consists of photographs of corneal topography produced as clinical data. The collection includes photos of eyes with normal vision, moderate keratoconus, mild keratoconus, and advanced keratoconus. The dataset is enhanced with data using the Keras Image Data Generator class. The Keras Image Data Generator class receives and alters a batch of training-related images. The original batch is replaced with the newly modified batch of photos after a series of arbitrary alterations are applied to each image in this batch.

As a result, the Image Data Generator only returns the newly modified data after accepting the original data and randomly transforming it. This can be derived from equation (1):

$$nout = [nin + 2p - k]/s + 1$$

Equation (1)

Where;

nin: number of input features
nout: number of output features
k: convolution kernel size
p: convolution adding size
s: convolution stride size

The basic objective of data augmentation is to improve the model's generalizability. The network can learn more robust characteristics because it regularly encounters fresh, slightly altered versions of the input data.

Simple geometric modifications, such as random translations, rotations, scale changes, shearing, and horizontal flips, can be used to create the augmented images from the source photos. The "In-place data augmentation" or "On-the-fly data augmentation" technique is used by the Keras Image Data Generator class. When a network is trained, using this type of data augmentation ensures that it sees fresh iterations of the data at each epoch. Applying this in-place data augmentation involves the following steps:

- The image data generator is shown a batch of input photos.
- Each image in the batch is subjected to a series of random changes by the Image Data Generator.
- The calling function is then given the batch that has been modified at random.

The Keras Image Data Generator class only returns the randomly altered data; it does not return both the original batch of photos and the transformed batch. Because this augmentation is carried out during training, it is known as in-place or on-the-fly. The examples are not produced beforehand or before instruction.

In Fig. 3, the models used are InceptionV3, Xception, MobileNet, DenseNet-121, DenseNet-169, and DenseNet-201. The augmented data is used to train and validate the models.

Network	Models Evaluated	Crops Evaluated	Top-1 Error	Top-5 Error
VGGNet [18]	2	-	23.7%	6.8%
GoogLeNet [20]	7	144	-	6.67%
PReLU [6]	-	-	-	4.94%
BN-Inception [7]	6	144	20.1%	4.9%
Inception-v3	4	144	**17.2%**	**3.58%***

Fig.3: Evaluation of Models

V. RESULTS

Using training and validation data, the developed model is assessed. The summary function enables users to view the model's layout and its various layers. The outcome is a table with four columns that lists the current layer's settings, output shape, kind of layer, and connected layer.

The models' accuracy results are as follows after 200 iterations of evaluation against training and validation data. The graphs below show the validation accuracy with loss and the training accuracy with loss for the last five epochs. The matplotlib library can be used to visualize the accuracy. The following line graphs illustrate the training and validation accuracy over 200 epochs.

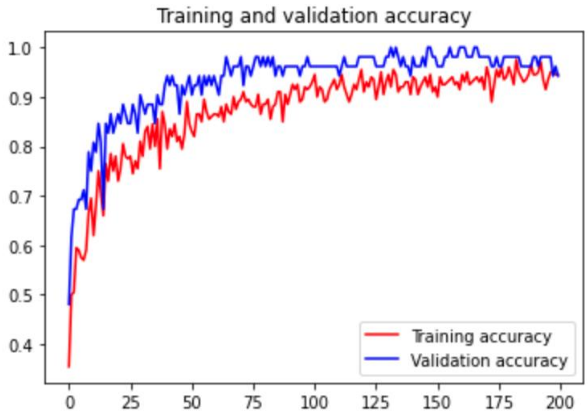

Fig. 4: Inception V3 Model

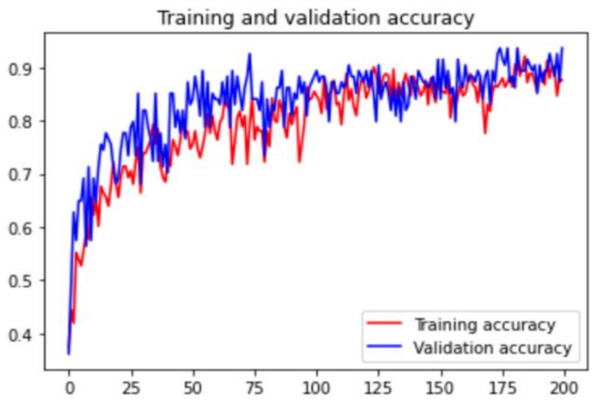

Fig. 5: Mobile Net Model

VI. CONCLUSION

The development and integration of assistant software to support ophthalmologists in the diagnostic process is the project's primary contribution. Machine learning algorithms have the potential to replace traditional medical screening systems, as they can quickly deliver diagnoses and enhance patient care and comfort.

To prevent disease development and visual loss, new diagnostic methods and instruments must be implemented as soon as possible. The suggested approach aims to improve quality of life and, ultimately, save lives by facilitating the early detection and classification of keratoconus, depending on its stage of progression.

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It can be concluded that a fast and efficient disease detection system can replace a manual system. The suggested solution addresses numerous drawbacks present in current systems, including time and financial requirements. This strategy can be applied in corneal clinics and research settings to enhance our understanding of corneal alterations in keratoconus, and to diagnose more accurately, track changes, and monitor progression.

FUTURE SCOPE

As a result of this effort, it will be simpler to diagnose severe conditions like keratoconus in the future. Additionally, since all relevant eye metrics were considered in the analysis, the same parameters can also be used to detect other underlying disorders. The device developed was successful in determining whether or not a person had keratoconus. The developed model can also predict the disease's severity, which ranges from 1 to 4 (where one is the least severe and 4 is the most severe). The model accounts for all the different scans currently performed by medical research to provide an accurate result for disease identification. With all eye-related factors, the accuracy attained is greater than 90%. Additionally, the dataset is used for in-depth multiclass prediction using the methods Naive Bayes, Gaussian, and SVC, together with generated macros and minute parameters. It is also possible to visualise the accuracy results after using the Linear Discriminant Analysis, Decision Tree Classifier, K-Nearest Neighbour, and Logistic Regression. The dataset itself can be further improved by adding photographs, removing undesirable ones, applying image preprocessing to enhance the photos, or refining the image content. A robust keratoconus detection approach based on smartphone camera images can be integrated into this algorithm to create a smartphone application. Through the use of scanning software that reflects rings onto the cornea, smartphone apps can enable the early detection of keratoconus disease by simply snapping a selfie or taking a picture with the smartphone's camera.

DECLARATION STATEMENT

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Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal contributions.

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AUTHORS PROFILE

Puja is an MTech student studying at RV College of Engineering, Bangalore. She specialised in Software Engineering during her MTech. She takes a great interest in the field of Artificial Intelligence and Machine Learning. She has undertaken various projects in the Artificial Intelligence and Machine Learning field, such as "Voice to Face recognition using GAN", "Test case predictor using BERT", "JIRA duplicate ticket suggester" and much more. Apart from this, she has worked as a Full-stack developer at leading IT firms and has a keen interest in front-end web frameworks, such as Angular and React. She also specialises in UI/UX with attention to detail. Currently, she works at an IT firm as a full-stack developer.

Dr. Ashwini K B has completed a Ph.D. in Computer Science and Engineering from Bharathiar University, Coimbatore, Tamil Nadu, India, in the year 2016. Her Ph.D. thesis title is "Data Aggregation in Wireless Sensor Networks". She has published 10 papers in international Journals, five papers in International Conferences, and authored three book chapters. She has conducted numerous hands-on workshops on Augmented and Virtual Reality, as well as Cloud Computing. She has submitted and executed several proposals at different levels, for example. Completed research project as Co-Principal Investigator - Centre for Upliftment and Personality Development of SC/ST Students for better outreach funded by AICTE, New Delhi. Currently Working as an Associate Professor at RV College of Engineering, Bengaluru, Karnataka, India.