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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 impacted by genetic, environmental, and ageing-related problems because they are one of the most complicated 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 necessitates a thorough examination of the cornea using a variety of methods, including slip lamp analysis and corneal tomography. The goal of the study is to identify and categorize keratoconus using a variety of machine-learning methods.***

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

I. INTRODUCTION

About one person out of 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][16][17][18][19][20]. The cornea then abruptly changes from its flat, dome-like shape to one that is more conical in shape and irregular in shape. The cornea's capacity to produce a clean image in the eye is deteriorating as a result of this shapeshift. In actuality, the irregularities in the corneal optics and the optical disturbances are getting worse with time. The primary goal of the model is to identify the earliest keratoconus manifestations in humans through various scans and feed that information into the system, which will act as a database for the model and enable it to determine whether a patient has keratoconus or not as well as 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. Similar to this, the majority of keratoconus (KC) sufferers' children do not have the condition, but they should be screened for it in the early adolescent years because early intervention will stop 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 fairly hefty molecule. For instance, as seen in Fig.1, it contributes significantly to the construction of your bone, muscle, and tendon tendons and ligaments. Keratoconus begins as a result of the corneal structure's fragility and progresses through time. Early keratoconus, moderate keratoconus, advanced keratoconus, and severe keratoconus are the four disease phases of keratoconus. This study's objective is to employ deep learning and machine learning to precisely categorise patients with KC [7].

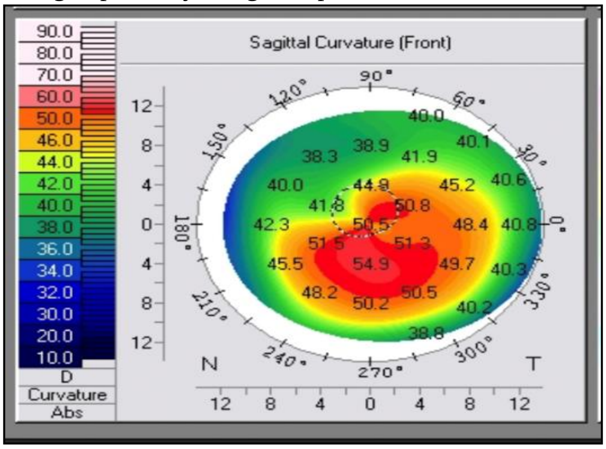

Fig. 1: Keratoconus Affected Cornea of a Sample

In this study, a CNN that was developed with the use of 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 aging-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.

The project's motivation is to use machine learning to identify eye conditions like 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 gives programmes the ability to organically take in and evolve 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 to be handled by Experts and topographical eye-images Identification. 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 to grow them. 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 by means of image processing techniques. [10].
Map (0.976) which discriminates against the normal 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 detects keratoconus disease automatically based on corneal topographies. In the tool that conducts the topography as an add-on, the algorithm may be introduced to support the ophthalmologist with a 99.3 per cent precision in the quick screening of his 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 allow the ophthalmologist to screen his patients rapidly, thereby reducing diagnostic errors and promoting the treatment. [12].
It claimed that the early stages of keratoconus are challenging to diagnose and that better outcomes can be obtained by the use of the height decentration index and the vertical asymmetry index. Twenty-seven individuals afflicted with uni-lateral keratoconus were followed up by their fellow eyes to assess initial markers of progress against keratoconus condition, which had not yet demonstrated any ectatic improvements. 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 the keratoconus status and severity can now be well defined utilizing automated unmonitored clustering algorithms utilizing topographic, tomographic, and corneal thickness profiles. We created an unmonitored machine learning algorithm and applied it too broad corneal parameters to classify and track keratoconus phases. Multiple centres throughout Japan have mounted a broad data set of swept corneal source optical coherence tomography (OCT) photographs of 12,242 eyes acquired from CASIA OCT Imaging Systems SS-1000. A total of 3,156 eyes were picked with an Ectasia Status Index (ESI) ranging from zero to 100 per cent Four hundred and twenty corneal topography, height, and pachymetry parameters (excluding the ESI Keratoconus indices) have been identified. [14] The algorithm encompassed three essential measures. 1) The primary component analysis (PCA) was used to minimize the input data dimensionality linearly from 420 to eight key components.2) Manifold learning was used to further reduce, nonlinear to two parameters, the selected main components. 3) Throughout the result, density-based clustering was extended to the own parameters in order to identify eyes with keratoconus. Visualization of clusters in 2-D space was used to subjectively test the learning efficiency, 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, process is a generalized one which is used on various architectures for comparative analysis.

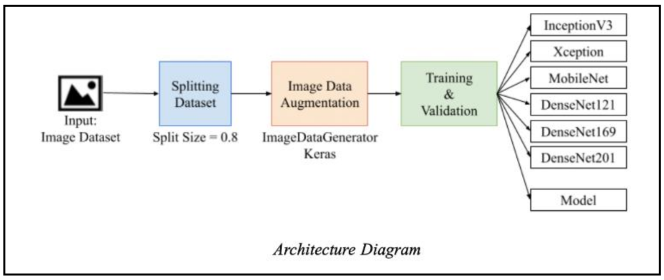

Fig. 2: Methodology of the solution

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.

The most common method for identifying and confirming keratoconus is to create a corneal topography, which is then analyzed by an expert ophthalmologist. These pictures will serve as our system's input. The dataset is made up of the photographs of the corneal topography that are produced as clinical data. The collection includes pictures 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 altered 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 by 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 is able to learn more robust characteristics because it regularly encounters fresh, slightly altered versions of the input data.

Simple geometric modifications like 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 guarantees that it sees fresh iterations of the data at each and every 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 are the InceptionV3, Xception, MobileNet, DenseNet121, DenseNet169, and DenseNet201 are the models that were used. 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 allows users to see the model's layout and different 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 5 epochs. The matplotlib library can be used to visualize the accuracy. The following line graphs illustrate the training and validation accuracy over 200 epochs.

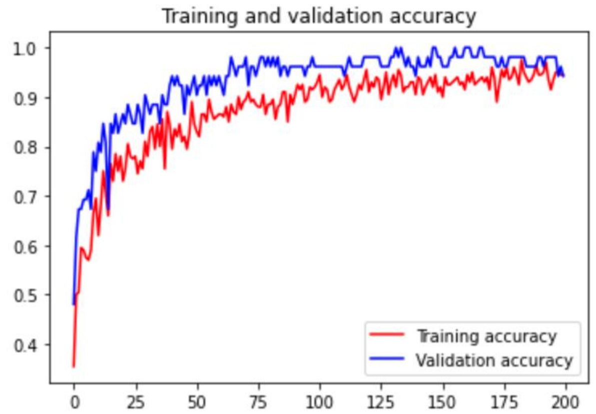

Fig. 4: Inception V3 Model

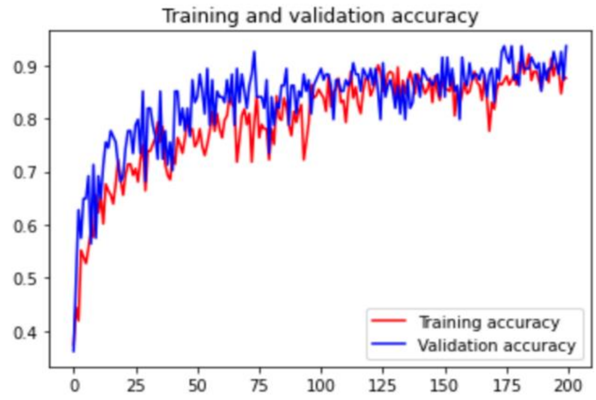

Fig. 5: Mobile Net Model

VI. CONCLUSION

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

To stop disease development and visual loss, new diagnostic methods and instruments must be put into use as soon as possible. The suggested approach intends to improve quality of life and, eventually, save lives by assisting in the early detection and classification of keratoconus depending on its stages.

It can be concluded that a fast and efficient disease detection system can replace a manual system. The suggested solution gets beyond numerous drawbacks present in current systems, such as time and money requirements. This strategy can be applied in corneal clinics and research settings to enhance our knowledge of corneal alterations in keratoconus and to better diagnose, track changes and progression.

FUTURE SCOPE

As a result of this effort, it will be simpler to diagnose serious 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 could also predict the disease's severity, which ranges from 1 to 4. (1 being the least and 4 being the highest). The model accounts for all the different scans that are currently performed by medical research to provide an accurate result for the disease identification. With all eye-related factors, the accuracy attained is greater than 90%. Additionally, the dataset is used for the 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 Neighbor, and Logistic Regression. The dataset itself can be improved further by adding photographs, deleting undesirable ones, using image preprocessing to enhance images, or narrowing down the content of the images. The robust keratoconus detection approach that is based on smartphone camera images can be added to this algorithm to create a smartphone application. Through the use of scanning software based on the reflection of rings onto the cornea, smartphone apps can enable early detection of keratoconus disease simply by snapping a selfie or a picture with the camera in front of the smartphone.

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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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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 like Angular, and React. She also specialises in UI/UX with attention to detail. Currently, she is working at an IT firm as a Full stack developer.

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