Evaluation of Deep Learning Networks for Keratoconus Detection Using Corneal Topographic Images

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Abstract. Keratoconus is an eye disease of 'deformation of corneal curvature' caused due to 'non-inflammatory progressive thinning' resulting into loss of elasticity in cornea and protrudes a cone shape formation that ultimately reduces visual acuity. For many years, researchers have worked towards accurate detection of keratoconus (KCN) as it is essential checkup before any refractive surgery demanding quick as well as precise clinical diagnosis and treatments of keratoconus prior to LASIK. In our study, we have firstly derived two variants of the original corneal topographies namely 'images with edges' and 'images with edges-and-mask', as data sets. The deep neural network techniques such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and pertained VGG16 model are applied on original 'corneal topographies' as well as on the two of its variants and the results obtained are presented.

Keywords: Keratoconus · Corneal topography · ATLAS 9000 · ANN · CNN · VGG16 · Canny edge detection · Edges with mask

1 Introduction

Cornea is transparent outer layer of eyes responsible for maintaining safety and shape apart from producing clear images by refracting light properly. So, any irregularities in corneal curvature reduces the quality of vision. As shown in Fig. 1, due to progressive thinning the cornea losses elasticity and turns into cone shaped formation that protrudes, referred as Keratoconus. In keratoconic condition, cornea distorts light refraction resulting into blurred vision. Keratoconus typically impacts both the eyes but starts impairing one eye first. In the advanced stages of keratoconus, the progressive thinning may lead to blindness. Keratoconus is asymptomatic in its early stages but the irregularities in corneal curvature are manifested gradually [1, 2].

Refractive surgery is suggested for correcting the eye's ability to focus but can only be performed on the healthy eyes by reshaping the corneal curvature. So only when the LASIK surgery performed on the eyes with keratoconic condition can cause corneal ectasia that may lead to irreversible damage [3]. The prevalence of Keratoconus is seen in the Arabic region as well as other Asian countries. Keratoconus can impact old as well as young so the early detection can help in preventing the irreversible damage [4–8]. Hence not only the early detection but the better methods of diagnosis of keratoconus is needed. As a result, over the past many years various algorithms and

S. K. Singh et al. (Eds.): CVIP 2020, CCIS 1377, pp. 367–380, 2021.
https://doi.org/10.1007/978-981-16-1092-9_31

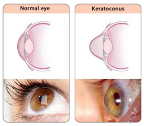

Fig. 1. Comparison between normal eye and keratoconic eye

models of neural network have been applied for detection and discrimination of keratoconus and the contribution of neural network models in classifying keratoconus is remarkable. However, the need for the enhanced methods with high accuracy has encouraged this research and application of deep neural networks on corneal topographies. The accuracy of the deep neural network model depends on the quality and nature of images. Belin et al. [9, 10] explain elevation-based topography and its advantages over Placido – based devices. A topography map reads features from corneal surface which plays significant role in detection of keratoconus. Additionally, such topographic maps provide information about location and shape of elevation on corneal curvature which is useful to detect the presence of the disease and its severity. The past researches suggest the need for not only detection of keratoconus but detecting this disease in its early stage to halt the progression of protrusion in cornea. As keratoconus is irreversible condition in its advance stages, effective methods for early detection of KCN may prove significant to restore the patient's vision.

In this study, we have extracted images with edges and images with edges and mask from the keratoconic corneal maps. The images with 'edges and mask' show the shape of elevated region or thinning of actual cornea and pattern developed due to irregularities in corneal curvature. In order to do so, it is required to separate the keratoconic maps from the normal corneal maps. Here, we have applied ANN, CNN and VGG16, a pretrained ImageNet model on our three derived variants of corneal topographies shown in Fig. 2. These variants are original color images, images with 'edges' and images with 'edges and mask', which are used in this study to compare the effectiveness of three deep learning models. These variety of images possess pattern of elevated region and shapes. The shapes and dispersal of elevated area, are useful for detecting the severity of the disease and may participate in early detection of keratoconus.

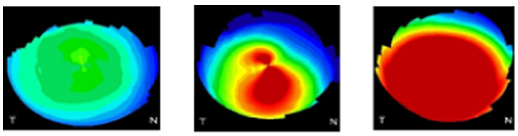

Fig. 2. Pre-processed topographic maps of normal eye and progression of keratoconus

2 Related Work

The Neural Network (NN), subset of AI, tries to imitate human brain and mostly chosen as prime technique to analyze and classify medical data. Armstrong et al. [11] explained the role of Artificial Intelligence and Machine Learning in various ocular diseases. Further, Smolek et al. [12] suggested the preference of NN approach over videokeratographic methods.

P. Agostino et al. [13] used NN to identify keratoconus from 396 corneal topographic maps selected from videokeratoscope (EyeSys), here parameters of both eyes were used to classify classes namely - 'Normal', 'Keratoconus' and 'Alterations'. They initially used 6 neurons where the result was not satisfactory and went ahead to use 9 and 10 or 19 neurons for unilateral and bilateral respectively which than appeared to improve the accuracy to 96.4%, primarily as the parameters used were from both the eyes. So, the identification of keratoconus in its early stage still remains an issue.

Advancement in AI and NN led to revolutionary Machine Learning technique which produced proficient outcomes with keratoconus [14, 15].

Valdes-Mas et al. [16] predicted vision accuracy of patient's with keratoconus, by measuring corneal-curvature and astigmatism, after intra-corneal ring implantation. They could achieve their best accuracy only after using multi-layer perceptron ANN method, notably an offshoot of Machine Learning.

There had many precedencies of Machine Learning being used for keratoconus classification. Souza et al. [17] used Machine Learning model to device SVM, multilayer perceptron and radial basis function, to evaluate performance for keratoconus identification, whereas, all three neural network classifiers were trained on Orbscan II maps. The outcome was based on ROC that shows similar performance by all three classifiers.

Arbelaez et al. [18] processed Pentacam images of eyes using SVM classifier for differentiating normal eyes from other three groups of eyes – Abnormal, Keratoconus and Subclinical Keratoconus. This classifier shows higher accuracy in detection of keratoconus compared to normal eyes, considering data with the posterior corneal surface and corneal thickness indices that made classifier effective for subclinical keratoconic eyes, important for detection early signs of disease.

Ali et al. [19] implemented SVM with topographic maps for classifying normal maps and maps with abnormal indications.

Kovács et al. [20] choose Machine Learning classification, by applying multilayer perceptron model on bilateral data from Pentacam Scheimpflug images. It can differentiate eyes with unilateral keratoconus from the eyes with refractive surgery, further suggests the need and importance of an automatic screening software to identify eyes with unilateral keratoconus, in early stages itself.

Toutounchian et al. [21] also used Image Processing on 82 corneal topographical images, obtained from Pentacam, for extracting the features. Multilayer-Perceptron, RBFNN, SVM and Decision Tree were used to classify images under Keratoconus, Suspect to Keratoconus and, Normal eye, with 91% accuracy. The image processing technique reads images as matrix of pixel where pixel values of images for Suspect to Keratoconus, could be helpful in early detection.

Hidalgo et al. [22] has applied SVM to process 22 corneal topography parameters for evaluation of accuracy of discrimination of normal eyes from keratoconus suspected eyes. Here also the weighted average of 95.2%, could be attained in separating keratoconus from the forme fruste keratoconus. They emphasised on increasing accuracy in diagnosis of asymptomatic subclinical patients. It can be noted that the use of subclinical keratoconus detection can be used to diagnose the early sign of keratoconus and hence helping in preventing the development and progression of disease.

Recently new substantial Machine Learning techniques have been devised to process the large amount of data. Based on the fusion of the concepts of Neural Networks and Machine Learning, the Deep Learning algorithms are much more capable to process large amount of data for analysis, prediction and classification.

Jmour et al. [23] suggested the significance of Convolutional Neural Network (CNN). CNN is well known Deep Learning technique widely used for image classification. CNN uses kernel, a small matrix of weights to perform convolution operation on the input images to classify the images by extracting its features.

Lavric et al. [24] 'KeratoDetect' model based upon CNN, detects keratoconus eyes with higher accuracy. Out of synthetic data of 1500 topographies of normal eye and 1500 topographies of eyes with keratoconus, 1350 topographies were used as training; 150 images were used for validation and 200 images to measure the accuracy of the proposed algorithm. As obtaining large data set was difficult, here, synthetic data were generated from 145 Scheimpflug topographies using SyntEyes KTC model. The size of epochs used was ten for 200 test corneal topographies, where each epoch used 21 iterations led to 97.01% accuracy. Similarly, 400 test topographies with 30 epochs was 97.67% and the accuracy improved only after increasing epochs to 38.

Neural Network (NN) has contributed enormously in the past, however, the recent techniques of Machine Learning and its offshoot Deep Neural Network has been proven to much more effective than NN in detection of keratoconus.

Lin et al. [25], observed that the detection of disease in early stage is difficult but essential for refractive surgery even with the imaging devices such as Topographic Modelling System, EyeSys, OPD-Scan, Orbscan-II, Pentacam and Galilei are being used to capture anatomic data from cornea. Imaging modalities as RT-Vue-100, Artemis-1 and Zernike coefficients could improvise detection accuracy. They further opined that apart from detection techniques, lack of standardized methods was leading to inconsistent dataset that resulted in improper definition of early manifestation of keratoconus. Also, public datasets of corneal topographies for keratoconus detection are insufficient which limits advance studies and research. They concluded that the Machine Learning techniques though performed better in distinguishing between keratoconus and normal, eyes, yet the machine learning alone could not differentiate a subclinical keratoconus and normal, eyes, efficiently.

Aforesaid studies illustrate the effectiveness of Neural Network techniques when applied upon topographic and tomographic data for keratoconus. Authors in this paper tried to apply the Deep Learning Techniques on corneal topographic data obtained from ATLAS 9000 topographic keratometer device, to detect keratoconus.

3 Study Data and Methods

It is observed that in the past studies, numerical measures and topographic maps were used frequently. However, with the evolvement of imaging and image processing technology, the recent studies are using corneal curvature elevation maps referred as topography and tomography images. The topographic maps consider anterior features of cornea whereas, tomography uses both anterior and posterior features as well. These maps are prepared from the digital images captured by keratometry device. Both types of maps are comprised of indices for corneal attributes especially elevation and steepening of corneal surface. The anterior segment indices represent measurement of the corneal surface and its morphology [10].

In our, this study, total 1104 colored topographic maps of cornea are extracted from ATLAS 9000 corneal topography device. This keratometry device has 22-ring Placido disk. It uses patented cone-of-focus alignment system and corneal wave front technology for analysis. The subject data consist of total 804 maps of bilateral keratoconic eyes from 402 clinically diagnosed patients and 300 healthy eyes from 150 patients.

The Axial curvature elevation maps are rendered using standard color scheme and normalized to size of $534 \times 534 \times 3$ pixels. The axial curvature map represents underlying local curvature irregularities and position of such irregularities. Topographic image data used here are clinically diagnosed with moderate to severe keratoconus condition. The forme fruste type of keratoconus maps are omitted from this study group.

This study consists of two sections: (i) Using OpenCV to derive edges and mask of elevated area from the corneal images to determine the effectiveness of dataset of corneal maps and its variants deriving to use in future for early detection of keratoconus disease and (ii) customizing deep learning networks to suit the purpose of achieving significant accuracy for keratoconus detection.

This study, as shown in Fig. 3, total of three data sets are used primarily, the originally derived ‘color topographic’ images and rest of the two being derived using canny edge detector to get images with ‘edges’ and ‘edges with mask’.

Fig. 3. Original color topography, image with ‘edges’ only and image with ‘edges and mask’

OpenCV is used to access the canny edge detector technique of computer vision. Computer vision is used to understand and extract the information from digital images to analyze and predict the visual data similar as the human brain functions. Using convolution techniques, canny edge algorithm reduces the noise, softens the edges by applying Gaussian smoothing technique and also determines the edges at the overlap of gradients. The overlapping of shades may affect the overall accuracy in detecting the interest of region and to resolve this a warm color area is identified as a mask signifying the higher intensity measure of steepening, present in the cornea, along-with its edges.

These newly processed images are referred as ‘images with edges and mask’. Topographic maps are derived in standard color scheme offered by ATLAS 9000 keratometer which ranges from cool blue color to warm red color, cool colors represent flatness and warmth the elevation highlighting protrusion of cornea. The shape of steepening or cone plays vital role in identification of the severity of keratoconus disease [26]. Previous researches suggest that certain corneal topographic patterns are well associated with prevalence of keratoconus [27], here in our research, the images with only-edges and edges-with-mask are further used to determine the accuracy of keratoconus detection.

We, in this paper, present use of three of deep learning techniques namely Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and pretrained ImageNet VGG16. ANN & CNN models are tailored with respective number of hidden layers to be used with three variety of data sets. Each model uses ‘ReLU’ activation function in its hidden layers to activate neurons of positive value in prediction and final layer uses Softmax as an activation function. Softmax normalizes the output from earlier layer and computes the probability ranges between 0 and 1 for each label. The ‘K-fold cross validation’ has been used with all the three algorithms to avoid over fitting. Every model uses 10 as a value of K. K - fold ensures that every observation from the original dataset has the chance of appearing in training and test set here. In each model, stochastic optimizer ‘Adam’ is used to update learning rate individually of deep neural networks. Being a combination of ‘AdaGrad’ and ‘RMSProp’, two derivatives of Stochastic Gradient Descent, ADAM works well with the large amount of data as well as with the deep learning models and CV problems. This optimizer handles the issue of vanishing gradient commonly seen while dealing with large amount of data. In this study, ADAM determines optimized learning rate for parameters in our network models that accept corneal topographical maps as input data.

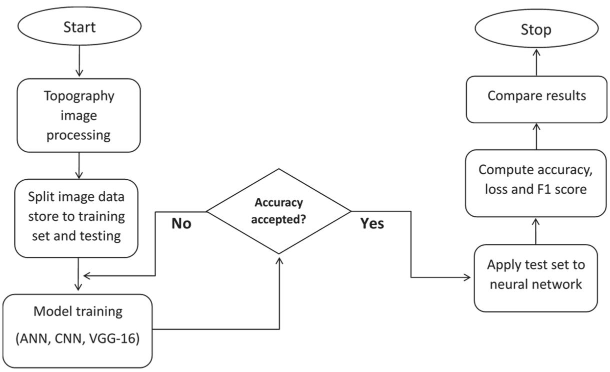

Fig. 4. The common workflow for all three models

Figure 4 represents the common workflow for all three models. As part of data preprocessing, the images read are reshaped, extra information is removed, further cropped and rescaled to 534 × 534 × 3 pixel. RGB images are converted into HSV format as being more compatible, to prepare both data sets for detecting specific colors.

4 Discussion and Results

Here, as depicted in Fig. 5, the ANN's tailored architecture uses (a) an input layer (b) two hidden layers with 64 and 16 neurons respectively along with 'ReLU' activation function in each of the layers and (c) an output layer with sparse categorical cross entropy function, to calculate the loss between predicted and actual, labels.

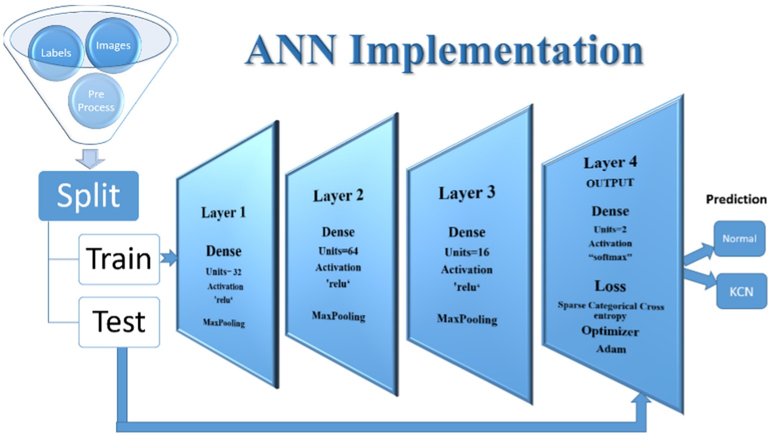

Fig. 5. ANN model: structure

Each hidden layer uses 'ReLU' activation to normalize neurons with positive values. ANN is applied with epoch size 5 and K-fold with all three sets of images with 10 as value of K. The best average accuracy achieved by ANN with data sets used in this study is 94.31%. The average performance of metrics of ANN with all three sets of images are shown below in Table 1.

Table 1. ANN K-fold: average performance metrics

Model type	Layers	Accuracy	Loss	Precision	Recall	F1-score
Original color	4	94.649	0.570	0.967	0.960	0.963
Edges & mask (color)	4	95.74	0.250	0.973	0.969	0.971
Canny edges (binary)	4	92.568	0.395	0.960	0.937	0.948

From the average performance of all the 10 folds it can be seen that the best performance of ANN has been achieved with edges-and-mask data set and even the average F1 score is as high as 97.1%. In Fig. 6, ANN's peak accuracy 98.2% can be seen at the 3-fold, with image type as edges-and-mask and the highest F1 score is 98.7%.

Further, to compare the effectiveness of ANN with our dataset, a deep learning model CNN is used. Being known for its effectiveness in image classification, CNN also requires much less pre-processing load as compared to other algorithms.

Fig. 6. Accuracy and F1 score obtained by ANN

Here, in Fig. 7, the architecture of our tailored CNN model can be seen. The input to the CNN (ConvNet) are color images of 534 × 534 × 3 pixels. This CNN model uses 3 × 3 kernel to execute convolution process. CNN model consists of 10 hidden layers out of which 4 layers use 32 filters and layer 5 uses 16 filters. In Convolutional layers, padding and stride size are set as 1 for training process that preserves useful information and decreases the dimension of data. Further, feature data are dealt by flatten layer and subsequently, the most relevant and potential features are handed over to the fully connected output layer that is a single dimensional vector ready for classifying data among keratoconus and healthy, cornea.

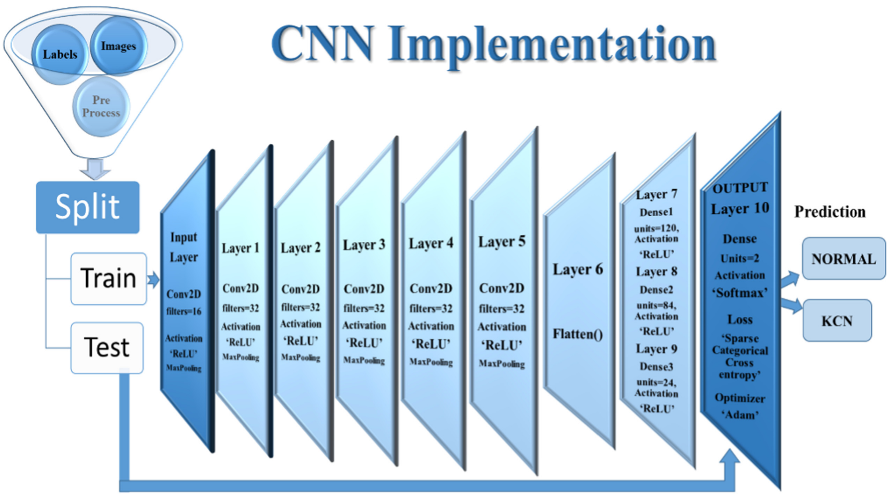

Fig. 7. CNN model: architecture

From Table 2, CNN model's average accuracy of 95.82% and the F1 score of 97.1% are seen as the best while applied with 10-fold cross validation on images with edges-and-mask. The Fig. 8 further illustrates the higher accuracy gained by this model for all three types of images. This model shows 99.09% as the best of its accuracy and F1 score of 99.3% for images with edges and mask at 2-fold. Also, its performance with color images and images with edges are equally good.

Table 2. CNN K-fold: average performance metrics of 10 folds

Model type	Layers	Accuracy	Loss	Precision	Recall	F1-score
Original color	10	95.742	0.149	0.984	0.957	0.970
Edges & mask (color)	10	95.825	0.146	0.980	0.963	0.971
Canny edges (binary)	10	94.931	0.163	0.966	0.963	0.965

There are numerous powerful ImageNet CNN architectures readily available to apply on variety of data. For assuring of the performances exhibited by ANN and CNN, a pretrained VGG16 model is used with the same sets of images for comparison.

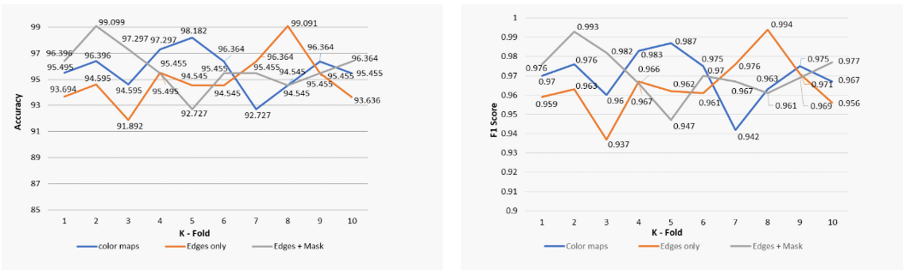

Fig. 8. Accuracy and F1 score obtained by CNN

VGG16 is ImageNet winner from year 2014 and considered as excellent vision model for image data.

VGG16 is appreciated for its simple and consistent arrangement of layers.VGG16 uses 3×3 filter with stride value 1 and same padding and structure of max pooling layers with 2×2 filter and stride size 2.

VGG16 uses 16 layers with weights and fully connected layer with SoftMax function to produce output resulted in very large network with approximately 138 million parameters. Vgg16 uses 64 neurons in input layer and settles with 512 neurons in last hidden layer as seen in Fig. 9. Here, VGG16 is applied with all three varieties of data prepared for classification.

Fig. 9. VGG16 model: architecture

As indices shown in Table 3, VGG16 model performs the best with 97.94% average accuracy among all three data sets used here. F1 score is the best for the original color types of images being 99.0% and average F1 score for all the three types of images is 98.5%.

Table 3. VGG16 K-fold: average performance metrics of 10 folds

Model type	Layers	Accuracy	Loss	Precision	Recall	F1-score
Original color	16	98.550	0.858	0.991	0.989	0.990
Edges & mask (color)	16	98.280	1.918	0.991	0.985	0.988
Canny edges (binary)	16	97.013	1.426	0.979	0.980	0.979

VGG16 model performs very well with original color images as well as images with edges with mask as shown in Fig. 10. VGG16 model with data set of 'edges and mask' images, scores 100% accuracy and 100% F1 score in 5th, 8th and 9th folds while applied with 10-fold cross validation. This model also scores 100% accuracy and 100% F1 score in 5th and 6th folds when performed on image data set of original corneal topography. Thus, VGG16 model exhibits better results with images having edges and mask as well as original color images packed with all features.

This research shows the detection of keratoconus with high accuracy using images with 'edges and mask' derived from the original dataset, which suggests the usability of these images in determining the shapes of steepening and curvature irregularities present in keratoconic corneal topographies. The analysis of the patterns and shape of elevated area manifested on corneal surface of keratoconic eyes help in the early detection of the keratoconus disease as well as identifying other corneal irregularities.

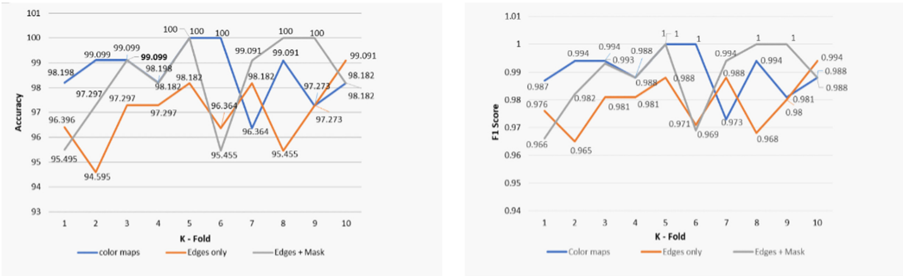

Fig. 10. Accuracy and F1 score obtained by VGG16

5 Analysis of Results

The Table 4, below shows the comparative performance of all three algorithms, ANN, CNN and VGG16 applied on three groups of images by comparing average accuracy and F1 score.

Table 4. Comparative chart of average performance metrics of ANN, CNN and VGG16

Model	ANN K-folds			CNN K-folds			VGG-16		
Value	Accu	Loss	F1-score	Accu	Loss	F1-score	Accu	Loss	F1-score
Colored original	93.66	0.49	0.956	95.74	0.15	0.970	98.55	0.86	0.990
Edge and mask (color)	95.74	0.25	0.971	95.83	0.15	0.971	98.28	1.92	0.988
Edge only (binary)	94.65	0.57	0.963	94.93	0.16	0.965	97.01	1.43	0.979

ANN performs best on images with ‘edges and mask’ with 95.74% accuracy and 97.1% F1 score while performance of CNN is also the best on images with ‘edges and mask’ with 95.83% accuracy and 97.1% F1 score which is slightly better than its performance on color topographies showing 95.74% accuracy and 97.0% F1 score. VGG16 performs the best with all types of images used, it achieves better accuracy on color images with 98.55% accuracy and 99.0% F1 score. VGG16 shows 98.3% accuracy with 98.8% F1 Score, which is equivalent performance of this model on images with ‘edges and mask’.

All the three models show overall good accuracy and F1 score applied on images with ‘edges and mask’. This result shows the effectiveness of images with ‘edges and mask’ for detection of keratoconus, which further suggests the use of this variant of corneal images for the early detection of keratoconus.

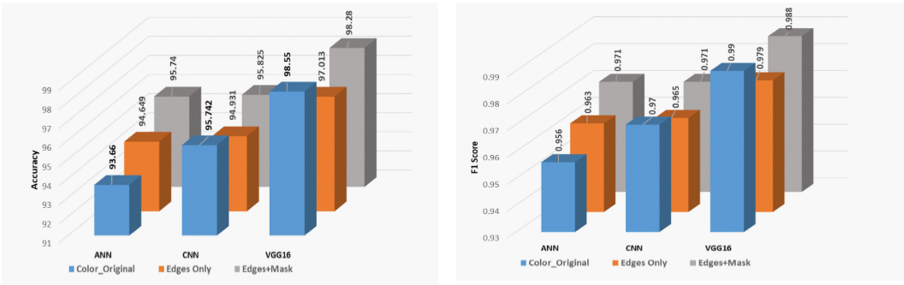

Fig. 11. Comparison of overall average accuracy and F1 score of ANN, CNN and VGG1

Figure 11 depicts the comparative chart of all three networks, ANN, CNN and VGG16. The performance of VGG16 is the best with all three types of images with respect to all measures. ANN and CNN perform the best with 'edges and mask' type of images and their performance on images with 'edges and mask' show similar F1 score measures. However, performance of all three models for images with 'edges and mask' is considerably good and consistent, that suggests the potential of images with 'edges and mask'.

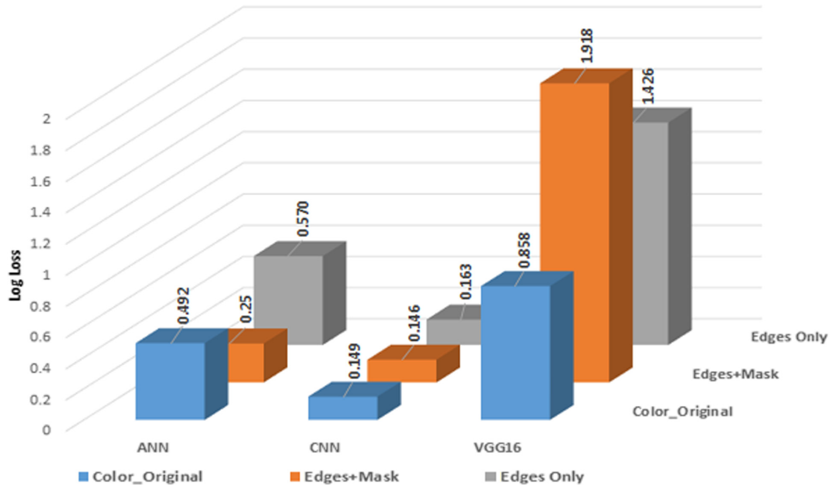

Fig. 12. Comparison of overall average loss of ANN, CNN and VGG16

It is seen in Fig. 12 that VGG16 suffered slightly higher log loss in 7 and 9 folds in case of images with 'edges and mask' and in 8-fold with respect to images with only edges.

Further, over all comparison of all the three models with their application on all three different types of images indicates that stability of CNN model is the best and is slightly better than that of ANN and it is much better than that of VGG16.

6 Conclusion and Future Work

It is evident from our work that all the three models ANN, CNN and VGG16 perform quite well with respect to different parameters namely accuracy, precision, recall and F1 score and can be utilized for detection of keratoconus. Stability with CNN model is the best, whereas VGG16 gives the highest accuracy and F1 score. The performance of all three models exhibits consistently good accuracy on our newly derived images with combination of 'edges and color mask' which suggests that these images can be used to identify the shape of the elevated region of corneal topography and further may help to enhance the diagnosis process by determining the severity of keratoconus. This manifestation from the corneal elevation maps in future can be useful to exhibit its role in the early detection of keratoconus.

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