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OCULAR DISEASE SEVERITY IDENTIFICATION AND PERFORMANCE OPTIMISATION USING CUSTOM NET MODEL

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Abstract. Early detection and timely cure of ocular disease play a vital role to avoid irreversible vision issues in daily life. The technique fundus assessment utilizes color fundus photography, which is a very effective tool though it is expensive. Since rare symptoms of the disease are detected at the initial stage of the disease, still automated and optimized models are in urgent need for the detection of the ocular disease. Additionally, existing systems focus on image-level detection for the treatment of eyes without association employing the left and right eye information. Although they concentrate only on one or two features of the ocular disease at a time. Taking into consideration severity detection and multilabel categorization plays a vital role in ocular disease detection. So, we develop a framework to detect the disease in the early phase. And then apply the classification model for the multilabel classification of the disease. our proposed experimental result proves that the proposed Custom net model provides 99.15% of accuracy compared to the existing baseline model such as Vgg16, 19, Resnet-50 and Inception V3. The performance optimization of the proposed model is evaluated on the public datasets.

Key words: Deep learning, ROP, Custom-net, Disease, Severity

1. Introduction. Retinopathy of Prematurity (ROP) is a disease occurs in premature babies having low birth weight. This causes blindness in such kids [11, 5]. The shorter the gestation or the lighter the birth weight, the more the chance of ROP disease. So, the factors viz. gestational age, birth weight and supplemental oxygen status helps in detecting the ROP [4].

The ROP screening should be done from time to time after birth of premature babies. It can be terminated once there is complete vascularization of retina without any ROP, or if the ROP has shown complete regression.The disease can be graded in terms of zone, extent in clock hour, stage of ROP(1,2,3,4a,4b,5), Aggressive Posterior (APROP) and disease status [1].

This paper proposes an elaborate design of a deep learning model to detect and classify ocular disease. The deep learning model is composed of three units: CNN model, feature extraction and classification. The CNN model is utilized for the extraction of the features from the datasets and feature extraction and image processing are utilized for the enhancement and synthesis of the features [26, 2]. The classification model creates the output of the classification. Our proposed deep learning model archives an inspirational performance on the ocular dataset. In this article, we broadly observe the results. Also, we discuss the performance parameters viz. accuracy, F1 score, Recall, Precision.

Our contribution is as follows:

- Proposed the deep learning neural network to identify the disease.
- A novel module, feature extraction, and image processing propose to enhance the different features from the datasets.
- Implementation of VGGNet-16,VGGNet-19 ,ResNet 50 and Custom net module on the ocular datasets. Also, utilized the Explainable AI to identify, whether this system is trustworthy or not. Fig 11 depicts the Explainable AI results, as you can see the results are not that accurate but in future we can improve

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it.Substantially optimized the performance of the model.
- Adam optimizer is used to optimize the results of the model.
- Compared the performance matrices such as accuracy, F1 score of VGG 16, VGG 19, and ResNet-50 and custom net model also proved that Custom net model achieves better performance compared to other models.

2. Literature Review. Although, there are different existing imagining technology to detect ocular disease Optical Coherence Tomography (OCT) and Color Fundus Photography (CFP) are widely utilized nowadays [25]. Cross-section images based on retina created by the OCT, to measure the eye condition the retinal thickness is utilized. CFP maintains the interior parts of the eyes to examine the possible syndromes. CFP and OCT tools have been confirmed to identify the early stages of the ocular disease [8]. Although, CFP is costly but effective tool for the adults because periodically fundus assessment of the adults provides symptomless result. However, some ocular diseases viz. diabetic retinopathy, macular degeneration based on age-related and cataract with very few symptoms are very difficult to diagnose at an initial stage. Furthermore, manual examination of the created huge scale of CFP is a very time-consuming process. So, an automated system is developed to detect at the disease at an early stage and also to improve the accuracy of the detection [3].

Deep Neural networks (DNN), especially Convolutional Neural Networks (CNN) have proven to play a vital role in the field of medical imagining[4]. Moreover, CNN has proven to diagnose ocular disease into various levels of disease classification as well as detection of an object. The detection of the fovea centre in the Oct image has been performed by the pixel classification approach. The optic disk in the field of CFP [20] has been detected through the CNN model i.e. based on two-stages. The authors suggested adopting CNN to analyse the fluid in OCT images. Also,the encoder-Decoder based network has been developed to measure the various retinal layers and also computes the collected fluid in different OCT images. The portion of the retinal vessels based on CFP is identified by both combined and fully connected CNN. The improvement of the accuracy is achieved by the image level observation to identify the segmentation of the retinal image [19]. The classification of the ocular disease by CNN has been more attention rather than object detection and segmentation [7]. The authors classified the ocular disease according to the severity levels of the disease.

The transfer learning model [15] such as image net and inception network was observed to be very successful to ocular disease classification into a different stage. A better classification result could be attained by the Ensemble learning.

Furthermore, there are very few words that refer to the problem of ocular disease classification based on multi-label [29]. Also, one single patient can be affected by multiple types of ocular diseases. Additionally, there is a high probability of the patients who are affected by multiple ocular diseases. So, there is a need to find the optimal model to get a better result and more classification of the ocular disease [27]. The authors have identified the existence of myopia, runs the high rate of false-negative value in glaucoma patients. Subsequently, the existing technology is generated to give acceptable result for the specific activity. But this technology is not appropriate for real-time situations [14]. Moreover, for the mentioned issue there are very less works on the ocular disease classifications [16]. There are existing publications that are mainly focused on the analysis of the CFP images that are generated from the left as well as right eyes [12, 21, 10]. However, detection of the disease of patients through pre-screening is very risky. So, it is not recommended for the long-term procedure.

The authors [18] proposed a deep supervision-based network for Retinopathy of Prematurity (ROP) detection and classification into mild, moderate, and severe classes. The authors utilized two ROP detection datasets obtained from Guangzhou women and children's medical center. First dataset contained 7396 fundus images which were used for ROP detection. The second dataset contained 1337 fundus images that was used for classification into three classes. The data had been collected from year 2012 to 2015. The data was annotated by three experienced pediatric ophthalmologists that labeled the data for detection and classification purpose and only consistent resultant images were considered for the training and testing phase. The authors found consistent results in annotation for detection purpose but variable results in annotation done for classification purpose due to subjective evaluation. The authors utilized DenseNet121 CNN for feature extraction in the initial phase. In DenseNet121, every layer of the network was connected to the first layer that helped it to reuse the features. Later, they embedded multi semantic feature aggregation into CNN to handle the problems of local redundancy and complex global dependencies. Lastly, they used deep supervised learning strategy in which they added

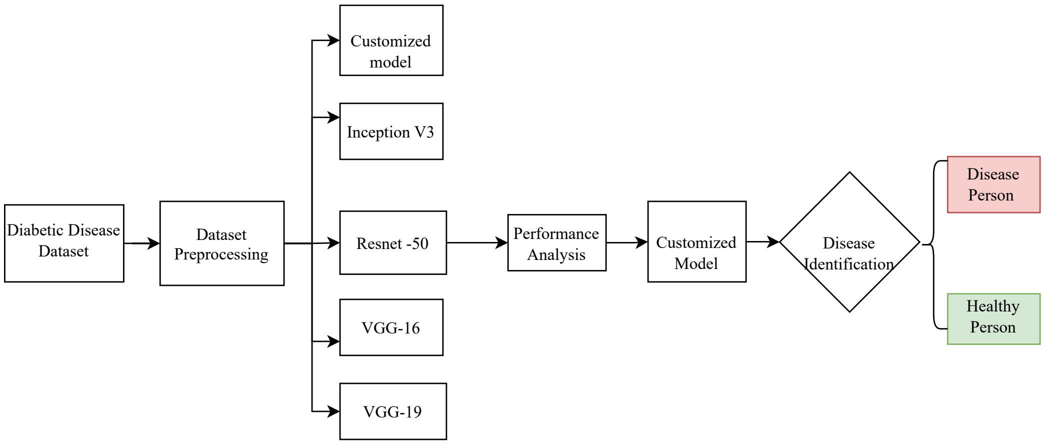

Fig. 3.1: Proposed Framework for Diabetic Disease Detection

two more auxiliary classifiers after the second and third stages in DenseNet121. This architecture benefited the system by providing full use of feature information in hidden layers and optimized the network. They used transfer learning to train the model due to small size of data. The system achieved an accuracy of 97.76% with recall and precision of 97.14% and 98.35% respectively. The proposed system outperformed many other CNN architectures such as DenseNet169, ResNet50, Resnext50 and InceptionV4. The classification process was tricky for experienced ophthalmologists and a challenge for system due to less amount of available data.

The authors [28] proposed an automated Aggressive Posterior-ROP (AP-ROP) diagnostic system that identified ROP from fundus images and classified them into normal ROP and AP-ROP. AP-ROP is a special type of ROP that evolved very rapidly in the fifth stage of ROP. The authors used dataset collected from Shenzhen Eye Hospital from 2009 to 2018 with 13,508 fundus images taken from RetCam3. The images were annotated by experienced ophthalmologists and shortlisted 12230 images based on good quality and clarity of ROP stages. Dataset consisted of 1698 AP-ROP, 4033 Regular ROP and 6499 Normal fundus images. it was divided into training, testing and validation set in the ratio of 54: 30:14. The authors used ResNet-18, 34, 50, 101 for feature extraction network and found all of them performing well in this case. The system used Hierarchical Bilinear Pooling (HBP) module that expanded the features of different layers to a high dimensional space by creating independent linear mappings in the network. Later, it integrated the features of different Convolutional layers through element-wise multiplication. Afterwards, the HBP module compressed high dimensional features using summation technique to obtain inter-layer interaction features. The system also used transfer learning to transfer the parameter learned by Network 1 to Network 2 to improve the classification performance of network 2. The system achieved accuracy of 98.88% with AUC value of 99.93% for task1. It had obtained an accuracy of 93.03% for task 2 using transfer learning mechanism.The authors proposed a solution for dealing with small files, the concept can be used in implementing database with Hadoop and can provide a simple way to store health data [22, 24, 23].

3. Methodology. In this manuscript, the authors propose a framework to detect the disease whether that person is healthy, disease diagnosed person. The proposed framework is categorized into three components. First component, Data pre-processing has been processed and then disease detection was done by different machine learning classifiers and custom net models. In this section, the authors explained about the proposed workflow, dataset, preprocessing, evaluation metrics and training details as shown in Fig. 3.1.

3.1. Dataset. Ocular Disease Intelligent Recognition(ODIR) is a structured ophthalmic of 5000 patients with Patient age, Patient sex, Left and Right Fundus, etc. data labels. The dataset represent real-life patient information collected by several doctors. The datasets classified as healthy,diseased (cataract, retina). At first, we downloaded the dataset from Kaggle, and required model weights were taken to indenfication of compatibility environment of VGG16 classification model. The image size should be 224*224 for the input of the model[17].

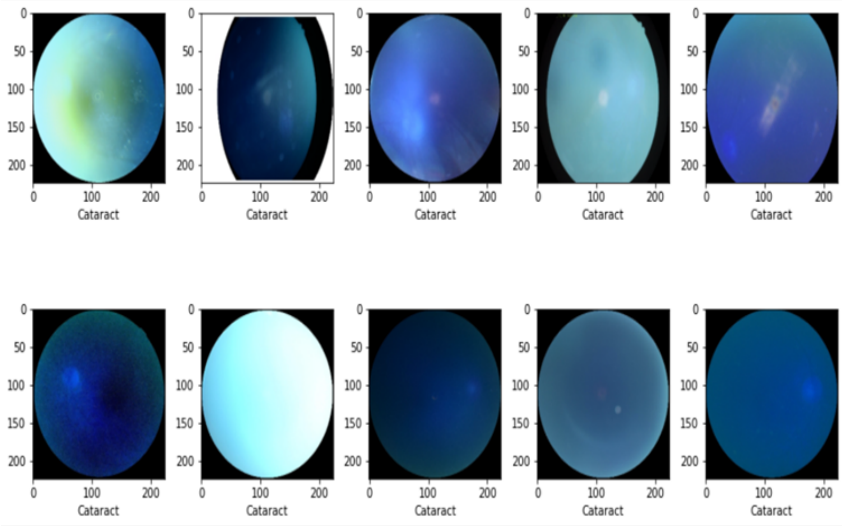

Fig. 3.2: Before augmentation

After that we performed some pre-processing on the images to make sure that the images are compatible with the model or not. It has been performed by the keras liberary with Data generator module.
To validate the system public ocular disease dataset is utilized. The dataset is divided into training set, testing set, and validation set as 80% training dataset, 10% as a testing set, and the remaining 10% for the validation set. The size of original datasets images is 3000*1700. Then by using image processing the size of the images is converted to 224* 224 dimensions.

3.2. Pre-processing. Cropped images are the input of data augmentation techniques. To get the left and right side of the image, augmentation is applied as shown in 3.2-3.3. Also, we applied the Gaussian filter to remove the noise and better visualization as shown in 3.4. The gaussian filter works on concept of Equation 3.1.

$$G(x) = \frac{1}{\sqrt{2\prod\sigma^2}} e^{\frac{x^2}{2\sigma^2}} \tag{3.1}$$

Here σ is the distribution of the standard deviation. Labeling performs a vital role to predict the classification of the image. It classifies the type of eye (either left or right) or type of disease as shown in Fig. 3.5.

3.3. Model architecture. The design of the "custom net" proposed to identify the diabetic disease dataset as shown in fig. consists of four convolution layers. Each convolution layer is supported by the max pooling layer. Additionally, the final max pooling layer is carried through the flattened and dense layer.ResNet model's different layers are used to extract the different features by utilizing CNN. The CNN [13] initialization is performed by the ImageNet. Ocular disease datasets are collections of 5000 images with different categories of the disease.

3.4. Evaluation Metrics. The classification of the ocular disease datasets is calculated with four evaluation matrices such as F1 score, TPR, FPR, accuracy,and Kappa score [9]-[6] as shown in Equation 3.2-3.8.

$$K = \frac{p_0 - p_e}{1 - p_e} \tag{3.2}$$

$$P_0 = \frac{\sum_{c=1}^{c} TP_C}{\sum_{c=1}^{c}(TP_C + FN_c)} \tag{3.3}$$

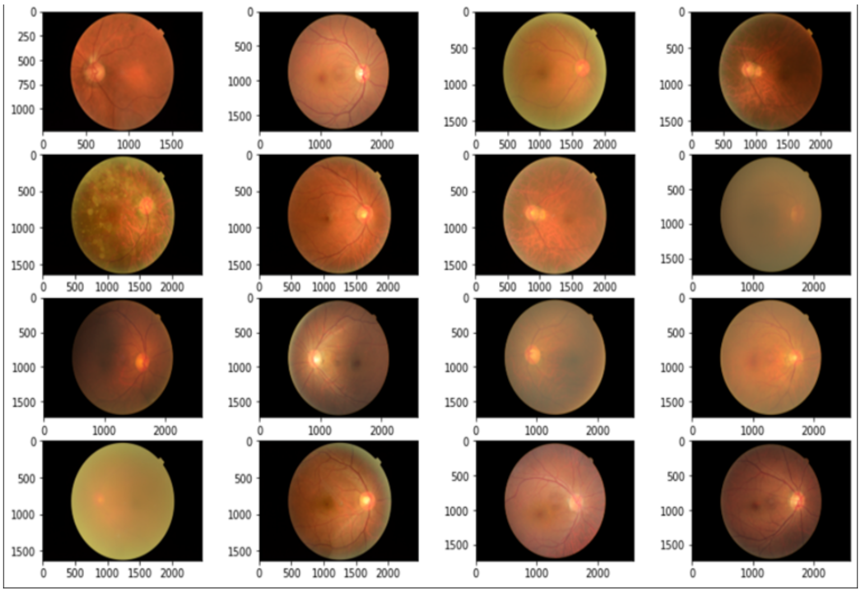

Fig. 3.3: After augmentation

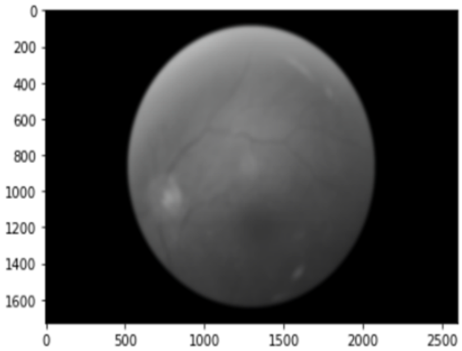

Fig. 3.4: Gaussian Filter for the thresholding

$$P_e = \frac{\sum_{c=1}^{c} TP_C * (Tp_c + FN_c)}{N^2} \tag{3.4}$$

$$TPR = \frac{TP}{TP + FN} \tag{3.5}$$

$$FPR = \frac{FP}{FP + TN} \tag{3.6}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Preciison + Recall} \tag{3.7}$$

$$AVG = \frac{1}{k + F1 + AUC} \tag{3.8}$$

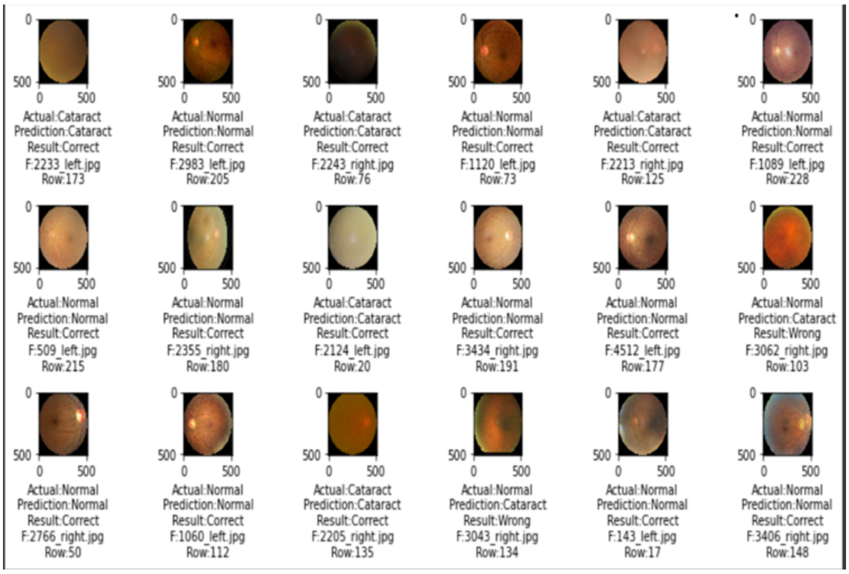

Fig. 3.5: Labeling prediction of left and right eye with the disease

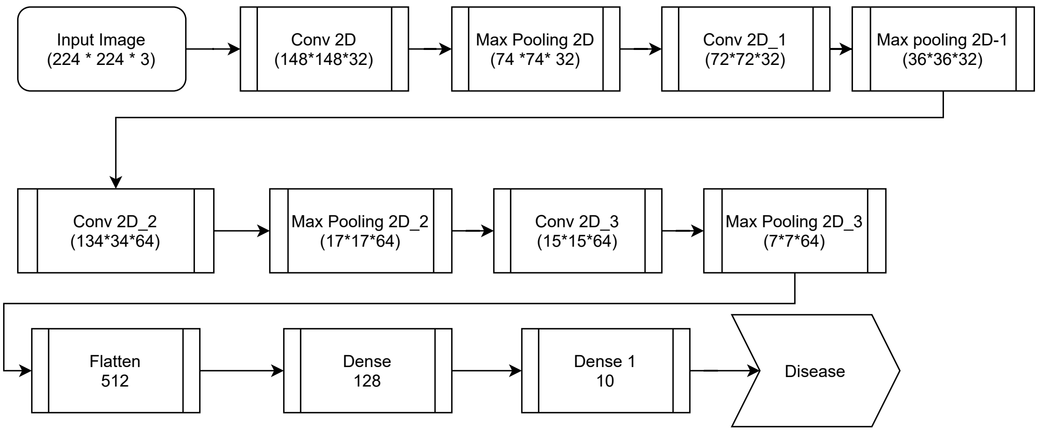

Fig. 3.6: Proposed Custom net Model

3.5. Training details. The Pytorch [17] is employed to implement the deep neural network. Models experiments are executed by NVIDIA 100Ti GPUs. For the optimization network, Adam optimizer is adopted to categorize into different classifications. The rate of learning is set as 0.0006, that is decay with decay policy lr = initially *(1-iter totaliter)power. The model power is set at 0.9. The complete experimental executed on 50 Epocs.

4. Experimental Results. In this section, the authors define the performance measurement of the custom net model based on the test data set, that is containing 5,000 images of dataset comprises of diabetic disease and healthy . They evaluate the pretrained and non-pre-trained versions of the deep learning model. The authors also evaluate the accuracy, F1 score, and precision and recall.

4.1. Average Accuracy. The Average accuracy calculates the pre-trained and non-pretrained versions of custom net mode and baseline models such as the Inception-V3, Resnet -50, and VGG -19,VGG-16.

The custom net model average accuracy based on non- pretrained version is 99.15%, and the pre-trained

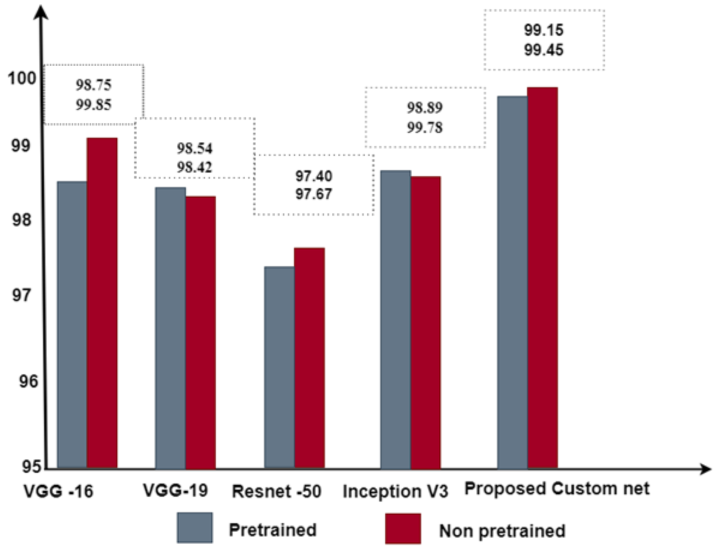

Fig. 4.1: Accuracy comparison with Custom net Model

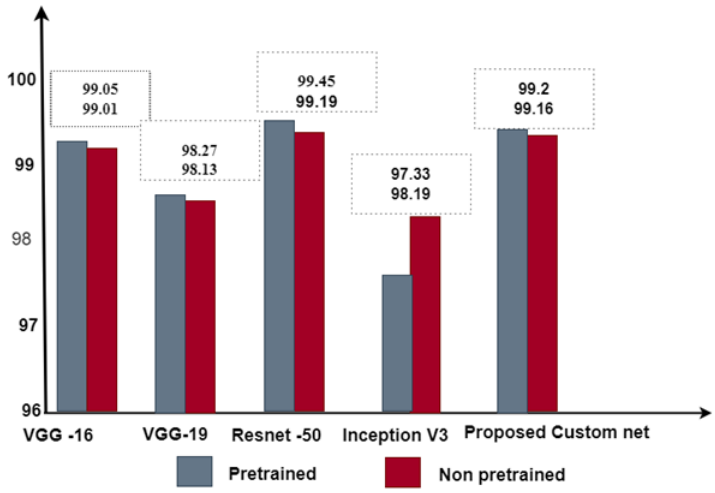

Fig. 4.2: Precision comparison with Custo net Model

model of custom net model accuracy is calculated at 99.45%. Similarly, the non-pre trained and pre-trained version of the Inception model V3 accuracy is reported as 98.89% and 98.79%. The Resnet -50 based on the non-pretrained model accuracy reported 88.30% in comparison to 97.40% of the pre-trained model. And the VGG -19 models report the average accuracy of pre-trained and non-pre-trained models are 98.54% and 98.42% as shown in Fig. 4.1.

4.2. Precision. The pre-trained model of the Resnet -50 provides the highest precision of 99.45% and there is a 0.26% percentage of the difference between the trained and non-pre-trained model of the Ressnet -50. Whereas the inception V3 model reports 97.33% accuracy of the pretrained model and 98.19% accuracy of the non-pre-trained model as shown in Fig. 4.2.

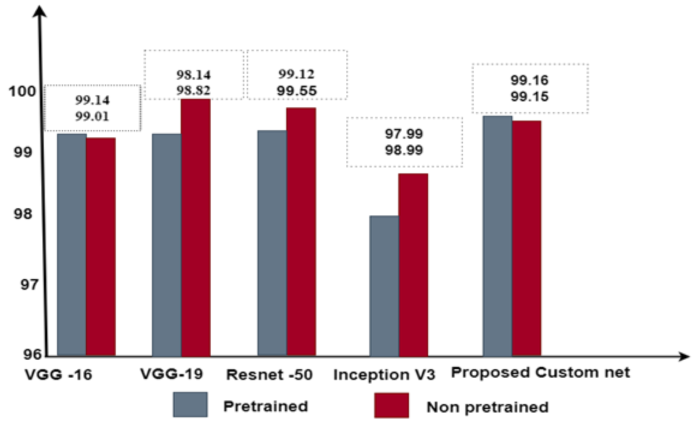

Fig. 4.3: Recall comparison with Custom net Model

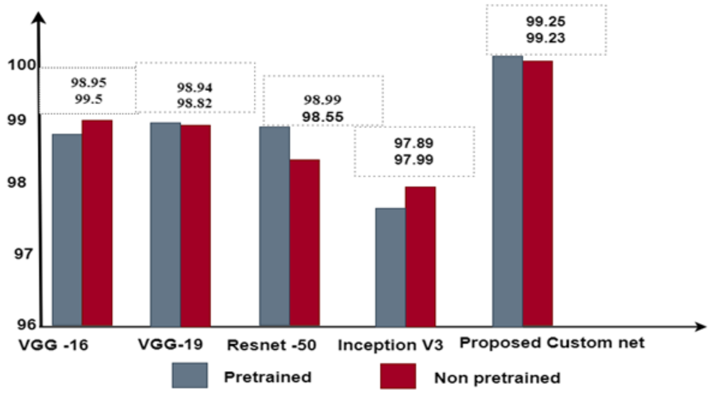

Fig. 4.4: F1-score comparison with Custom net Model

4.3. Recall. The custom net model average recall value of the non -pretrained version is 99.16%, and the pretrained model of custom net model accuracy is calculated as 99.15%. Similarly, the non- pretrained and pretrained version of the Inception V3 model accuracy is reported as 99.99% and 98.99%. The Resnet -50 based on non-pretrained model accuracy reported as 99.55% whereas 99.12% of pretrained model as depict in the Fig. 4.3.

4.4. F1-score. The custom-net model reports 99.25% of F1 score through pre trained model and 99.23% of accuracy through non pretrained model. Whereas inception V3, Resnet -50, VGG -16 and VGG -19 report the F1 score are 97.89%, 98.99%, 98.94%, 98.15% through pre-trained model. The proposed custom model achieves the highest F1-score among other models as shown in Fig. 4.4.

5. Conclusion. In this article, we proposed a method to detect the ocular disease and classify it into different phases according to the severity of the disease. The pre-processing phase include the feature extraction, augmentation, and labializing of the datasets. Additionally, we applied the gaussian filter to remove the unwanted noise. An ocular set of datasets is used for the predication of the disease. The classification of the disease is processed by the custom net model, VGG16, 19 and Resnet -50 and inception V3 and it is proved that proposed custom net model provides the better result compared to existing baseline model. still there are some limitations, that will be addressed in the future studies. Firstly, the proposed model can also be implemented on the other disease classification such as cancer, pneumonia disease. Secondly, this model was not compared with other existing image processing methods for the better classification. Thirdly, it can be implemented on the rest of CNN module to identify the better accuracy.

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