

## Eye Diseases Classification Using Deep Learning

<sup>1</sup>Mrs. T. Naga Mani, <sup>2</sup>B. S. S. N. K. Maha Lakshmi, <sup>3</sup>V. Teja Sri, <sup>4</sup>V. Vishal, <sup>5</sup>V. S. P. Deepak

<sup>1</sup>Associate professor, Department of CSE, SRGEC, Gudlavalleru

<sup>2</sup>Undergraduate student, Department of CSE, SRGEC, Gudlavalleru

<sup>3</sup>Undergraduate student, Department of CSE, SRGEC, Gudlavalleru

<sup>4</sup>Undergraduate student, Department of CSE, SRGEC, Gudlavalleru

<sup>5</sup>Undergraduate student, Department of CSE, SRGEC, Gudlavalleru

### Abstract:

Eyes are the most significant metaphorical sense organ. They have the potential to signify vision, knowledge, and a portal into the soul. Eyesight and vision are crucial because they allow us to connect with our environment, keep us secure, and help us preserve mental sharpness. Cataract, glaucoma, and diabetic retinopathy are the three most prevalent visual problems. Because of the increased incidence of these disorders, an early and correct diagnosis is required. The purpose of this study is to automatically identify photos containing cataracts, glaucoma, and diabetic retinopathy without the need of any intentional segmentation or feature extraction. Rather, we constructed and structured it so that patients could easily identify cataracts, glaucoma, and diabetic retinopathy. The network design is both simple and quick. The accuracy of this model has been found to be 94.55%.

**Keywords:** Cataract, Glaucoma, Diabetic Retinopathy, Deep Learning

### Introduction:

Eyes are complicated bodily parts that enable animals, humans, insects, and a variety of other organisms to view their surroundings. The eyes are key sensory organs. The problem with the eyes greatly decreases one's quality of life. If the individual goes blind as a result of an eye injury or ocular disease, the family, society, and country will suffer tremendously. Globally, there are at least 2.2 billion people who have near- or farsightedness. At least one billion of these cases, or around half of them, had visual loss that might have been avoided or ignored.

Early-onset severe visual impairment in young children can have a lasting impact on their motor, verbal, emotional, social, and cognitive development. Lower levels of academic success can also be shown in school-age children with vision impairment. Adults with vision problems typically have decreased workforce participation and performance, as well as greater incidence of depression and apprehension. Elderly people who lose their vision may experience social exclusion, limited mobility, a higher chance of falling and fractures, and a higher likelihood of entering medical or care facilities before they are ready. Age-related amblyopia, cataract, diabetic retinopathy, glaucoma, and uncorrected refractive errors are the main causes of visual impairment globally.

### Normal

The USC equivalent of 6/6 vision, which is 20/20 vision, is a reference value at which visual acuity is deemed normal: A human eye with that capacity can distinguish contours that are 1.75 mm apart at a distance of 6 meters (20 ft). You can easily see at 20 feet what you would normally see at that distance assuming you had 20/20 vision. The fundus picture of a healthy eye is shown in Fig. 1(a).

### Cataract

A cataract is a hazy spot in the eye's lens that impairs vision. One or both eyes may be affected by cataracts, which frequently progress slowly. Some signs of the condition include fading colors, hazy or double vision, halos surrounding lights, difficulty with bright lights, and difficulty seeing at night. This may cause difficulty driving, reading, or recognizing faces. In summary, several conditions, such as ageing, genetic predisposition, immunological and metabolic anomalies, trauma, radioactivity, and many others, can lead to lens metabolism problems, which can induce lens protein oxidation and opacity. Fig. 1(b) shows the fundus picture of an eye with cataracts.

### Diabetic Retinopathy

Diabetic retinopathy is a condition that diabetics might acquire. Eventually harm is done to the retina, the light-sensitive lining in the rear of the eye. When the blood and other fluids escape from these small blood arteries, it happens. The retinal tissue swells as a result, causing vision to become hazy or blurry. In Fig. 1(d), a diabetic retinopathy eye's fundus picture is shown.

### Glaucoma

An eye condition called glaucoma can harm your optic nerve. Although it's not always the case, extremely high pressure within your eye might cause glaucoma. Your optic nerve tissue may degrade over time as a result of the increasing pressure, which might cause vision loss or even blindness. It is an eye condition brought on by an increase in intraocular pressure (IOP). IOP rises as a result of fluid accumulation in the eye, which damages the optic nerve. Glaucoma is a chronic illness that, if not treated promptly, can harm ganglion cells and lead to permanent blindness. Early detection may allow you to stop further eyesight loss. Figure 1(c) illustrates a fundus photograph of an eye with glaucoma.

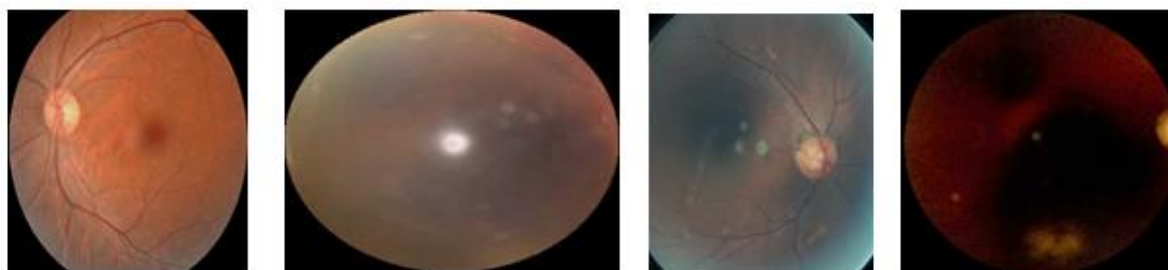


Figure 1: (a)Normal (b)Cataract (c)Diabetic Retinopathy (d)Glaucoma

The suggested approach is created and designed to make it simple for individuals to detect eye conditions such as glaucoma, cataracts, and diabetic retinopathy. People will benefit from early diagnosis and good treatment of various illnesses, which will lower the prevalence of blindness as a result. The earlier these diseases are discovered, the easier it is for the physicians to treat them, as the more difficult it is to treat a condition that has progressed to a more advanced level.

### Literature Review:

Diabetic retinopathy classification using efficient nets. Classify the stages in the diabetic retinopathy using deep learning. Classify the diabetic retinopathy as mild, moderate, no diabetic retinopathy and severe [1]. Retinal eye disease detection using deep learning. It mainly focuses on the diagnosing the diseases by feature extraction and then classifying the image. Instead of doing explicit segmentation or feature extraction, the fundus picture was automatically classified using a deep learning network [2].

Glaucoma is an eye illness that, if left untreated, might cause major harm and eventually lead to blindness. Glaucoma is sometimes referred to as the "secret destroyer of sight". This study offers a summary of several glaucoma detection techniques from a medical and machine learning viewpoint [3]. The greatest strategy to reduce the danger and prevent blindness is by accurate and prompt identification of cataracts. Systems for detecting cataracts based on artificial intelligence have attracted scientific interest. This research proposes CataractNet, a revolutionary deep neural network, for automated cataract identification in fundus pictures [4].

A novel family of convnets called EfficientNetV2 outperforms earlier models in terms of training speed and parameter efficiency. Studies have shown that EfficientNetV2 models train up to 6.8 times quicker than state-of-the-art models despite being much smaller [5]. Efficient Nets, which are more accurate and efficient than older ConvNets. For instance, our EfficientNet-B7 surpasses the most well-known ConvNet while reaching cutting-edge 84.3% top-1 accuracy on ImageNet by being 8.4 times smaller and 6.1 times quicker at inference [6].

Layers upon layers make up the Dense Convolutional Network (DenseNet), which uses a feed-forward connection to function. Our network features  $L(L+1)/2$  direct connections as opposed to traditional convolutional networks, which have L layers and L connections, one between each layer and its subsequent layer. Moreover, they greatly reduce the amount of parameters, improve feature reuse, and solve the vanishing-gradient issue [7].

A complete classification model for fruit fly was created behind the scenes using the convolutional neural network and SVM (CNN-SVM) model. It can automatically extract the useful picture pixels as a feature using the CNN technique, and then classify using an SVM model [8].

**Methodology:**

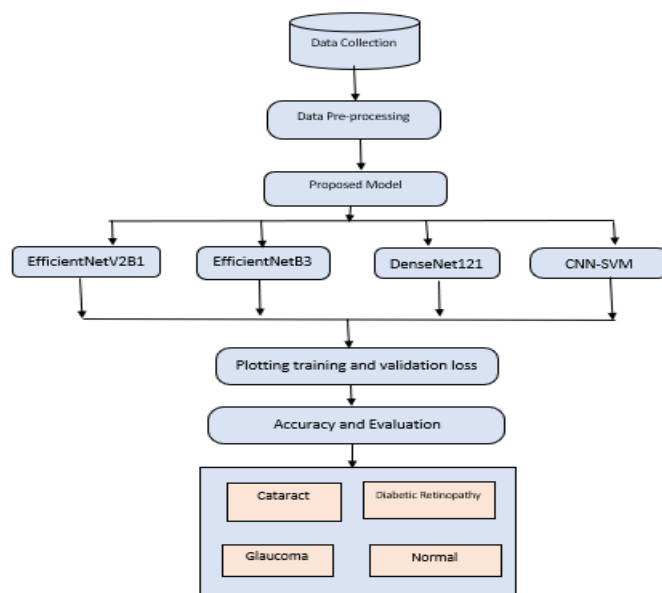


Figure 2: Our Architecture

By creating a comparable ensemble model, this study aims to create a framework for the automated categorization of eye illnesses. We employed the EfficientNetV2B1 model, EfficientNetB3 model, DenseNet121 model and CNN-SVM model as illustrated in Fig. 2. In later sections of the text, each step will be detailed in detail.

**1)Data Collection –**

First, we gathered eye fundus photos of eyes with cataracts, retinopathy caused by diabetes, glaucoma, and healthy eyes. Fundus photography involves taking pictures of the fundus, or the rear of the eye. Specialized fundus cameras, which combine a complex microscope with a flash-capable camera, are used for fundus photography. On a fundus image, the macula, optic disc, and peripheral and central retina may all be clearly seen. Using colored filters or dyes like fluorescein and indocyanine green, it is possible to visualize the fundus. There are 1038 photographs of cataracts, 1098 images of diabetic retinopathy, 1007 images of glaucoma, and 1074 images of healthy eyes in the collection.

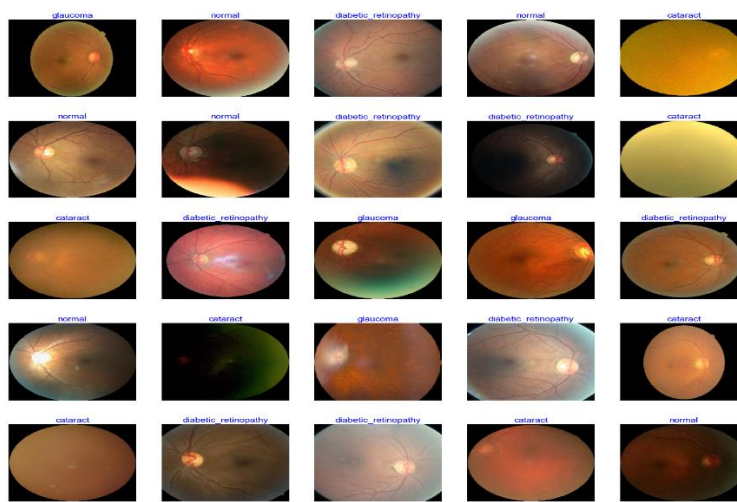


Figure 3: Eye Diseases Dataset

**2) Data Preprocessing –**

The process of converting unprocessed data into an efficient, comprehensible format is known as data preparation. Real-world or raw data frequently contains human mistakes, irregular formatting, and is occasionally incomplete. Such problems are fixed by data preparation, which also improves the completeness and effectiveness of datasets for data analysis.

The initial data used to train algorithms for machine learning is known as training data. These data are used by models to develop and improve their rules. A machine learning model's parameters are fitted to a series of data specimens in order to train the model using examples.

A well-organized dataset called test data provides information for each sort of situation the model could encounter in the actual world. A collection of data kept apart from current training data is the validation data. While training a network, it is used to test how well it would function with data that hasn't been explicitly used to train it.

The eye illness dataset includes 1038 photographs of cataracts, 1098 images of diabetic retinopathy, 1007 images of glaucoma, and 1074 images of healthy eyes. These pictures are categorised into training, testing, and validation data frames. Now, every class can have a maximum of 700 samples and a minimum of 700 samples. The shortened data-frame now has 4 classes and is 2800 bytes long. Both the training data and the validation data were enhanced.

**4) Model Selection –**

**A. EfficientNetV2B1–**

EfficientNetV2 model, with or without weights that have already been learned. Internally, the EfficientNet base class from torchvision.models.efficientnet is used by all model builders. Modern models train substantially more slowly than EfficientNetV2 models, which can be up to 6.8 times smaller. The Memory requirement for EfficientNetV2B1 is 34 MB. When referring to the model's performance on the ImageNet validation dataset, the top-1 and top-5 accuracy are used. EfficientNetV2B1 has a top-1 accuracy of 79.8% and a top-5 accuracy of 95.0%. The EfficientNetV2B1 operates with 8.2 million parameters in total.

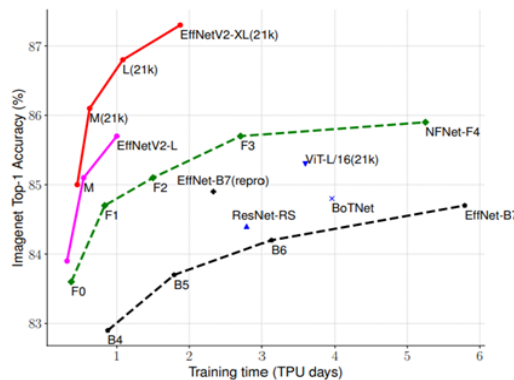


Figure 4: EfficientNetV2B1

**B. EfficientNetB3–**

In order to train a powerful feature extractor, each fundus image must first be processed using a strong CNN as the initial component to extract features. A little feature vector representation is what will come out of this. At the moment, the majority of CNN development is focused on fixed development resources. If the processing capacity is sufficient, the network will continue to expand. Using easy-to-use, efficient composite coefficients, All of the depth, breadth, and resolution parameters were scaled uniformly using EfficientNet. Using ImageNet and five well-known transfer learning datasets, EfficientNet also beat both cutting-edge systems, using orders of magnitude fewer parameters and floating-point operations per second (FLOPS). Using the exceptional efficiency of EfficientNet, we created a multi-label classification model for fundus photographs.

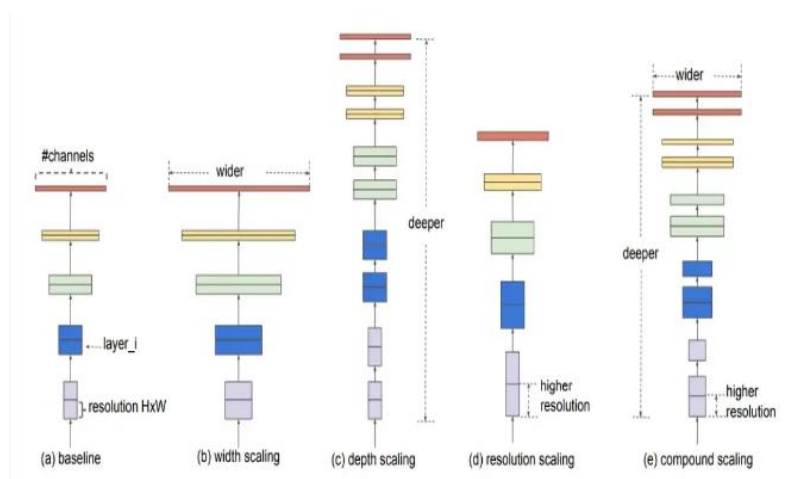


Figure 5: EfficientNetB3

Model	EfficientNet-B3
Top-1Acc.	81.1%
Top-5 Acc.	95.5%
#Params	12M
Ratio-to-EfficientNet	1x
#FLOPS	1.8B

**C. DenseNet121-**

The phrase "Densely Connected Convolutional Network" refers to a network where each layer is closely coupled to every other layer. Layer 'L' has L(L+1)/2 direct connections. DenseNets address this issue by adjusting the typical CNN design and streamlining the connection structure across layers. Four Average Pooling layers, one Fully Connected Layer, sixty-one 1x1 Convolution levels, fifty-eight 3x3 Convolution layers, and one 7x7 Convolution layer make up DenseNet-121. DenseNet-121 hence contains four Average Pooling layers and 120 Convolution layers.

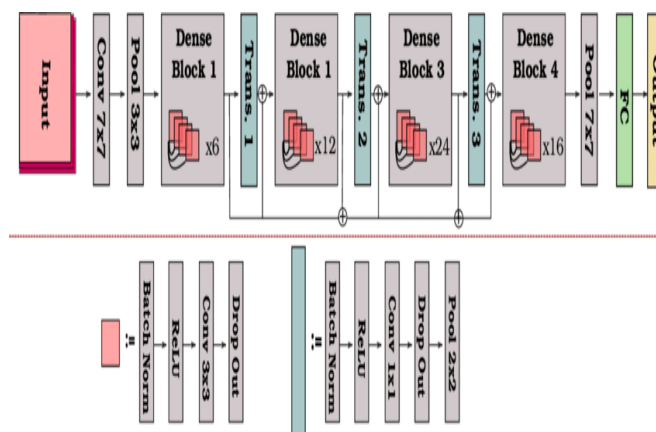


Figure 6: DenseNet121

**D. CNN-SVM-**

CNN, one of the most widely used deep learning models at the moment, is frequently utilised in computer vision research for tasks like target identification and picture categorization. CNN trains the multi-layer network that is used to retrace the mistake. BP and forward propagation connection weights and settings are being changed. Utilizing weight-sharing features through convolutional training decreases the duplication of parameter computation. Also, pooling accelerates forward propagation. By reducing the error through gradient descent, the BP approach is used to update and enhance the weights and parameters.

The Support Vector Machine approach of Supervised Machine Learning is used for regression and classification (SVM). Classification is where it is most frequently employed, despite the fact that it may occasionally be quite beneficial for regression. Essentially, SVM finds a hyper-plane that makes a separation between the different kinds of data. In two-dimensional space, this hyper-plane is nothing more than a line. The total number of features and attributes in the dataset, N, is used to plot each dataset item using SVM in an N-dimensional space. Then, the data should be divided using the ideal hyperplane. There are several ways that may be used for multi-class problems.

A complicated background fruit fly classification model was established using the convolutional neural network and SVM (CNN-SVM) model. It can automatically extract the useful picture pixels as a feature using the CNN technique, and then classify using an SVM model.

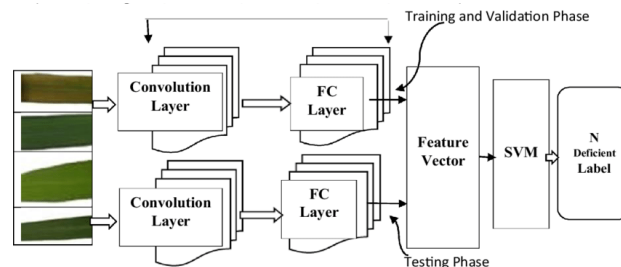
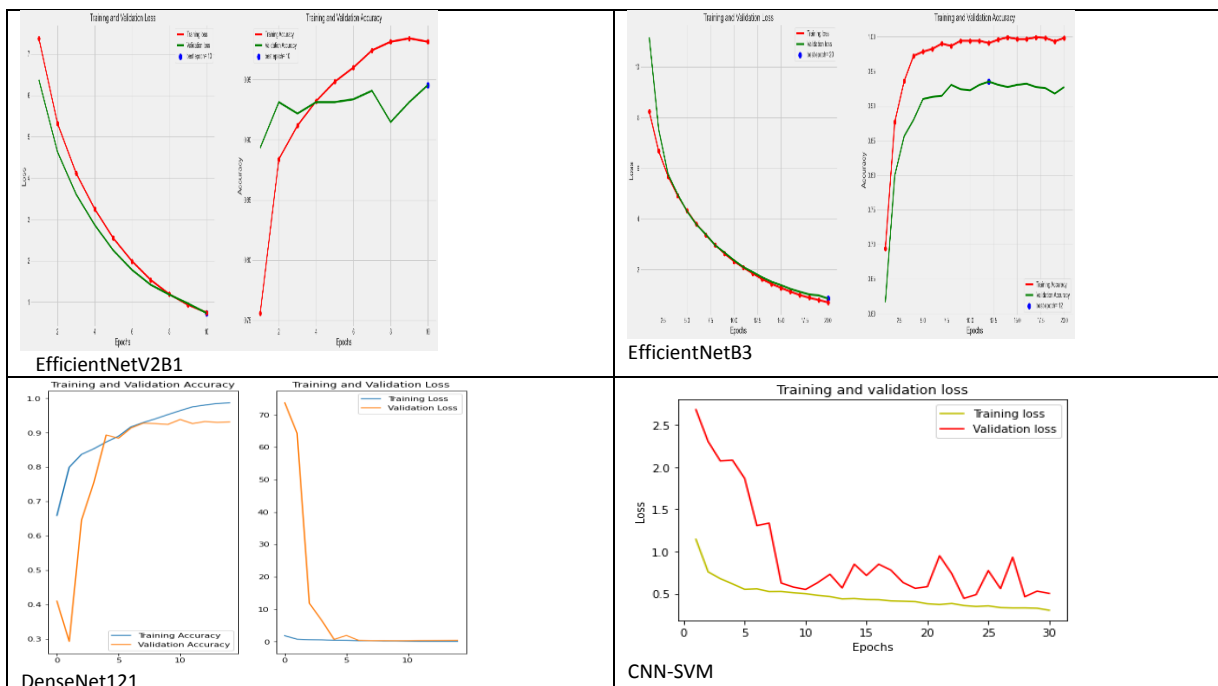


Figure 7: CNN-SVM

**Plotting Training and Validation Loss:**

The training loss statistic is used to assess how well a deep learning model fits the training set of data. It evaluates the model's accuracy by contrasting its performance to the training set. The training set is a subset of the dataset that was actually used to train the model, so keep that in mind. By adding together all of the mistakes for each sample in the training set, the training loss is computed. Also, it's critical to keep in mind that every batch yields an assessment of the training loss. The best method to illustrate this is typically by showing a training loss curve.

An evaluation of a deep learning model's performance on the validation set is given by its validation loss. The validation set, a subset of the dataset, was used to assess the model's performance. The mistakes for every sample in the validation set are added together to produce the validation loss, which is comparable to the training loss. Each session is concluded with an assessment of the validation loss. If the model has to be adjusted or updated further, this makes it evident. The most popular technique for accomplishing this is to create a learning curve for the validation loss.



**Accuracy and Evaluation:**

The proportion of samples that are properly classified is the most basic evaluation criterion for classification issues. The likelihood that a sample will really be positive among all those that are predicted to be positive is known as precision. Recall rate, which pertains to the original sample, is the probability of being accurately predicted as a positive sample in the actual positive sample. The kappa coefficient is a statistical consistency indicator that may be used to assess categorization accuracy. The F score is determined by averaging recall and accuracy harmonically. When the f1 score is near to 1, which is the average f1 value, the score indicates great performance.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{FP + TP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6)$$

$$\text{F1\_score} = \frac{2TP}{2TP + FP + FN} \quad (7)$$

**Comparison of Model Performance:**

In just 10 epoch, the EfficientNetV2B1 model generated accuracy of 94.55%. As opposed to CNN with SVM model, which generated 88.05% accuracy in 30 epoch, DenseNet121 model produced 93.12% accuracy in 15 epoch, EfficientNetB3 model produced 91.17% accuracy in 20 epoch.

Model	Accuracy
<b>EfficientNetV2B1</b>	94.55%
<b>DenseNet121</b>	93.12%
<b>EfficientNet B3</b>	91.7%
<b>CNN-SVM</b>	88.05%

**Conclusion & Future Work:**

Deep learning has demonstrated superior approaches and outcomes in increasing health systems and the capacity of eye screening in several clinical applications in specific and well-defined fields. The approach we have presented works better in those circumstances since we have encountered several difficulties that have an impact on the treatment of various diseases, including cataract. Because it is entirely software-based, the price is lower. The process of developing the sources for mobile applications may be included in future work.

**References**

[1] S. S. Karki and P. Kulkarni, "Diabetic Retinopathy Classification using a Combination of EfficientNets", *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Pune, India, 2021, pp. 68-72, doi: 10.1109/ESCI50559.2021.9397035.



- [2] Lorick Jain, H V Srinivasa Murthy, Chirayush Patel, Devansh Bansal, "Retinal Eye Disease Detection Using Deep Learning" .Authorized licensed use limited to: University of Newcastle. Downloaded on June 03,2020 at 11:46:51 UTC from IEEE Xplore.
- [3] A. A. Salam, M. U. Akram, K. Wazir and S. M. Anwar, "A review analysis on early glaucoma detection using structural features", *2015 IEEE International Conference on Imaging Systems and Techniques (IST)*, Macau, China, 2015, pp. 1-6, doi: 10.1109/IST.2015.7294516.
- [4] M. S. Junayed, M. B. Islam, A. Sadeghzadeh and S. Rahman, "CataractNet: An Automated Cataract Detection System Using Deep Learning for Fundus Images," in *IEEE Access*, vol. 9, pp. 128799-128808, 2021, doi: 10.1109/ACCESS.2021.3112938.
- [5] Tan, Mingxing, Le, Quoc V, "EfficientNetV2: Smaller Models and Faster Training". doi: <https://doi.org/10.48550/arXiv.2104.00298>.International Conference on Machine Learning, 2021.
- [6] Tan, Mingxing, Le, Quoc V, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks".doi: <https://doi.org/10.48550/arXiv.1905.11946>.International Conference on Machine Learning, 2019.
- [7] [Gao Huang](#), [Zhuang Liu](#), [Laurens van der Maaten](#), [Kilian Q. Weinberger](#). "Densely Connected Convolutional Networks".doi: <https://doi.org/10.48550/arXiv.1608.06993>.
- [8] S. Y. Chaganti, I. Nanda, K. R. Pandi, T. G. N. R. S. N. Prudhvith and N. Kumar, "Image Classification using SVM and CNN," *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)*, Gunupur, India,2020,pp.1-5,doi: 10.1109/ICCSEA49143.2020.9132851.