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Ocular Disease Recognition using Deep Learning

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***Abstract*— Artificial intelligence holds a significant impact in a variety of drug-related medical studies, including ophthalmology. Deep literacy styles, in particular, have been successful in detecting clinical signs and bracketing optical conditions. Studies reveal Ocular diseases to be the major contributing reason of childhood blindness all over the world. Rapid and automatic illness identification is vital and urgent in lowering the strain of ophthalmologists. Ophthalmologists use pattern recognition to identify disorders by looking at the eye and its surrounding tissues directly or indirectly. As a result, can benefit the area of medical greatly. Each disease has several severity levels that can be identified by confirming the presence of different lesions. Morphological characteristics identify each lesion, and numerous lesions from different diseases have similar characteristics. In ophthalmology, deep literacy techniques have mostly been employed on eye fundus pictures and optic consonance tomography. In this paper , we have used three models namely CNN, Inception V3 , VGG-19 for cataract prediction.**

We have got accuracy of 0.9587 for VGG-19 which is performing best as compared to other models.

Keywords- Clinical Diagnosis, Deep Learning, Image Classification, Neural Network, Ocular disease.

I. INTRODUCTION

According to the World Health Organization (WHO), 2.2 billion people worldwide are blind or have vision loss, with at least 1 billion having impaired eyesight that might be corrected.[1] Reports reveal that DED, a chronic eye illness can cause irreversible vision impairments if left untreated and if ignored for longer time, and this is estimated to be detected in around one-third of diabetics.[2]

Fundus pictures can be used to acquire retinal images, which aid doctors in evaluating lesions or changes in architecture. In such scenario, manual identification has been attempted but in longer way. Automation of these operations can save time and money.[3] The most serious tumors in the eye are iris cataract tumors, commonly known as 'eye tumors.' Cataracts are caused by a change in the tissue that makes up the lens of the eye as a result of age or damage. The lens' proteins and fibers continue to break down, resulting in hazy or poor vision. [4].

Cataracts can be aggravated by inherited genetic defects that create health concerns. The term ocular is used to describe a tumor that is accompanied by an eye. It can be intraocular (affecting the inside of the eye) or extraocular (affecting the outside of the eye). Cataracts, diabetic retinopathy, and redness level are the most common diseases detected. [5]. Through studies including automatic recognition of diseases from iris and fundus or retinal images, computer vision and deep learning have assisted ocular pathology. [6]

Elloumi et al. divide such research into two categories based on the goal: pathology or severity identification and ocular lesion segmentation. Fundus based images including ocular diseases have been included in their analysis of DL-based techniques, they mention works including Fundus image databases that target specific disorders.

These properties have allowed deep learning to outperform standard methods in a variety of computer vision and image analysis tasks. Because of its success, it is now being used to analyze medical images, including, of course, ophthalmology images [8].

The primary cause of blindness in the globe is fundus image disorders. Eye problems, age-related eye problems (AMD), glaucoma, and diabetes mellitus are among the most common eye illnesses (DR). According to projections, there would be 95.4 million people with cataract and 3.36 million of people with myopia by 2030, up from 1.95 billion in 2010. [9] Furthermore, according to various studies, those who develop myopia before the age of 20 are more prone to get cataracts later in life. Despite the fact that the specific cause is uncertain, some studies suggest that the increased axial eyeball length may hinder nutrient transfer to the lenses' rear site. [10]

We have focused on one of the ocular diseases that is Cataract. Firstly, we extracted images from dataset and resized images. Then we extracted information of whether eye is cataract affected or not. Then we trained Deep Learning models and compared accuracies of model to determine best performing model. We have discussed about this in Section IV Methodology.

II. LITERATURE REVIEW

In [14], mentioned various methods about how to classify diabetic retinopathy. A recommended profound learning framework called Deep Convolutional Neural Network (DCNN) involves spatial examination to give high exactness in infection distinguishing proof. A DCNN is a more convoluted plan in view of human visual discernment. Our proposed engineering, when joined with dropout layer draws near, accomplishes a precision of 94-96 percent.

In [25], Sarki looks at a range of automated methods for identifying diabetic eye condition. They have provided a complete eye detection overview of methods along with cutting edge field methodology, including cutting-edge field methodology, with the purpose of delivering vital information to research communities, healthcare professionals, and diabetes patients. It is classified as a black box since it is unknown. Several researchers have fine-tuned the restrictions of current deep learning algorithms like CNN to improve classification efficiency.

In [16], the ocular image is prepossessed using the HE method and the changed image is segmented using k-means clustering. SVM and RF are useful for categorizing the typical and unusual parts of the ocular picture, as well as reducing human error, which reduces false recognition and improves precision. When compared to the SVM, the identification rate of RF is 96.62 percent, indicating a great and steady result.

The neural network-based ocular pathology signs and disease identification approach is an innovative, practical, and intelligent alternative to traditional methods for early detection of optical diseases. It is a symbol of using image processing for the greater good of humanity. It has a high degree of accuracy in detecting all sorts of ocular disorders. It is been implemented practically and user friendly to use. This illness detection method has been put to the test in real time on a variety of photographs with various forms of ocular disorders, and thus bears the stamp of practical capability. Medical research and ophthalmology will benefit greatly from this study. [17]

Glaucoma is considered as one of the most dangerous eye illnesses. Glaucoma causes loss of eye site and is evident in the human eye. Glaucoma is a very serious illness that can cause blindness. If it is not curved in its early stages, it may cause blindness. As a result, detect this condition, a mechanism that relies on the deep neural network learning for the analysis, CNN is suggested. The proposed mechanism is based on a six-layer structure. CNN will work as cauterizing pattern according to the architecture. The patient's eyes were examined for signs of glaucoma. images of the eyes.[18]

In [19], they discorded a method to detect Diabetic Retinopathy and Glaucoma at an early stage. This system primarily serves as a referral trigger, informing the patient that a retinal expert should be consulted if a positive result is detected. A test set and real-time photos are used to test the less complicated pre-trained model. The accuracy rate was set at 80%. Using parameter tweaking and cross-validation techniques, this accuracy may be improved even further. The system also offers a graphical user interface that is simple to use and understand (GUI).

In [20], they employed a kernel-based VGG network model in this paper to achieve better outcomes in deep learning networks, and the training model in this proposed VGG network would not be merged but would be connected before being transferred to the layers. The fundamental concept was to connect all levels directly to ensure maximum information transfer across the network.

In [23], it proposes a profound brain network model to help location of beginning phases of diabetic retinopathy and glaucoma. It can notify people that they should see an ophthalmologist for a screening. This system primarily serves as a referral trigger, informing the patient that a retinal expert should be consulted if a positive result is detected. This newly designed model is less difficult and has an accuracy of 80%.

In [21], the proposed method in this paper uses three separate convolution neural network (CNN) models to analyze OCT images of the retina to identify the various retinal layers, recover critical information, detect any new abnormalities, and predict many eye diseases. This research demonstrates how deep learning techniques (CNN) may be utilized to correctly categorize and identify ocular illness traits such CNV, drusen, and DME in comparison to normal.

III. METHODOLOGY

A. Data Collection:

The dataset contains images of left and right eyes of almost 5000 patients. Information such as age, gender of each patient is also mentioned along with color fundus images.

Quality control management was used to mark annotations by trained human readers. Patients are categorized into eight categories, including:

1. Normal (N),
2. Diabetes (D),
3. Glaucoma (G),
4. Cataract (C),
5. Age-related Macular Degeneration (A),
6. Hypertension (H),
7. Pathological Myopia (M),
8. Other diseases/abnormalities (O)

B. Data Preprocessing –

1) We are using information related to cataracts and normal in our research. Then we are creating dataset from images along with that also resizing images.

IV. OVERVIEW OF PROPOSED MODEL

We have implemented 3 models namely CNN, VGG16, and Inception V3, and interpreted results from them.

A. Convolutional Neural Network: -

A convolutional neural network has an architecture similar to the human brain. It contains layers where each layer is connected to the next layer through neurons. It uses the convolution method which produces a function that helps in understanding how a change in one is affecting change in another.

Finally, ConvNet's task is to compress the images into a more manageable format while maintaining key components for a good prediction. Convolutional neural networks are made up of many layers of artificial neurons. Neurons are mathematical functions which calculate the weight of each input and give an activation value which helps in deciding whether a neuron will fire or not. When you input an image into a ConvNet, each layer develops several activation functions that are passed on to the next layer.

B. VGG 19: -

A 3x3 receptive field and 19 convolution layers make up the VGG-19 network. There are five of these levels, each with a 2x2 Max pooling layer. Three fully linked layers follow the final Max pooling layer,aafter that, three fully connected layers are added. It uses the softmax classifier as a final layer. All hidden layers have their Relu activated. The VGG19 model has the disadvantage of being expensive to evaluate and requirees a lot of memory and parameters.

VGG19 contains almost 138 million parameters. The majority of these parameters (about 123 million) are in fully-connected layers, which are substituted in our model by an SVM classifier, greatly lowering the number of required parameters.

C. Inception V3: -

Google Net published Inception V3 in 2014, a CNN-based Deep Learning model. This model contains 42 layers and has a lower error rate than its predecessors. It uses an auxiliary classifier to spread label information throughout the network and has 7x7 convolutions. It employs RMPS optimizers and includes label smoothing, a king of regularizing component that is introduced to the loss formula to keep the network from getting outliers in a class and this prevents over-fitting in the model that gives best results.

V. PROPOSED MODEL ARCHITECTURE

We have proposed 3 deep learning models namely CNN, INCEPTION V-3, VGG 19 for cataract prediction and following is the model architecture summary for each model.

Proposed model architecture: -

A. CNN -

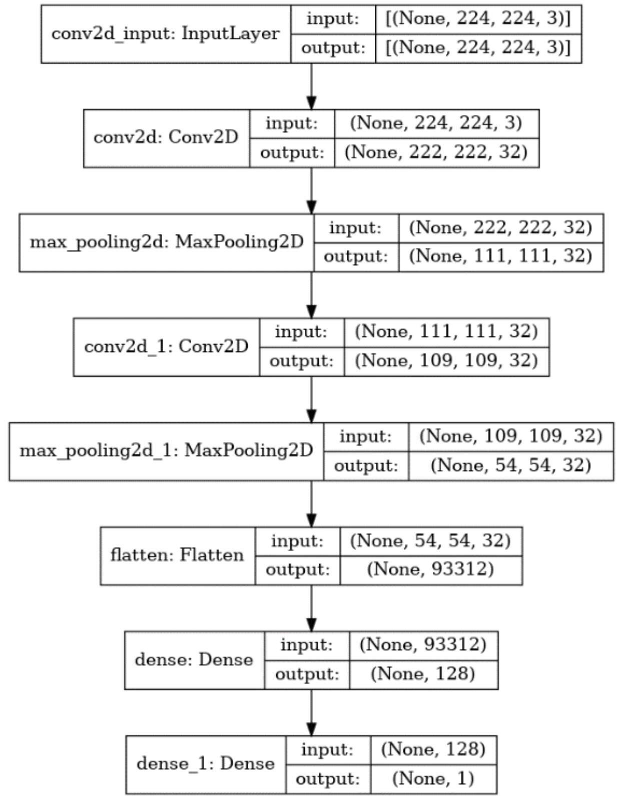

Fig. 1. CNN Architecture

B. VGG 19 -

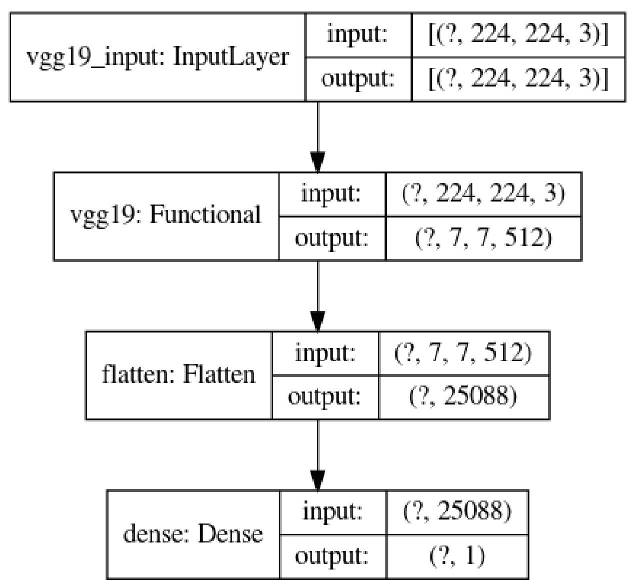

Fig. 2. VGG 19 Architecture

C. INCEPTION V3 -

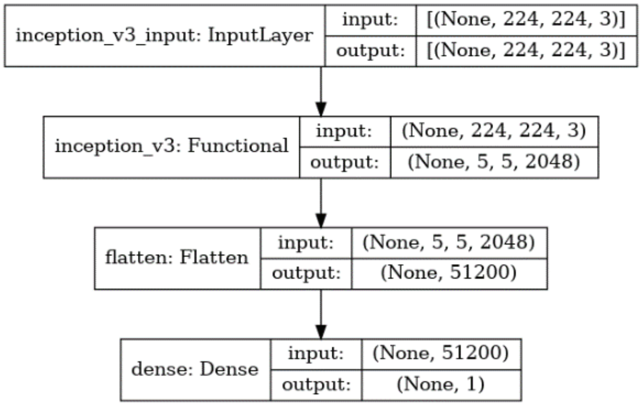

Fig. 3. INCEPTION V3 Architecture

VI. RESULTS AND DISCUSSIONS

The results which we have obtained are as follows –

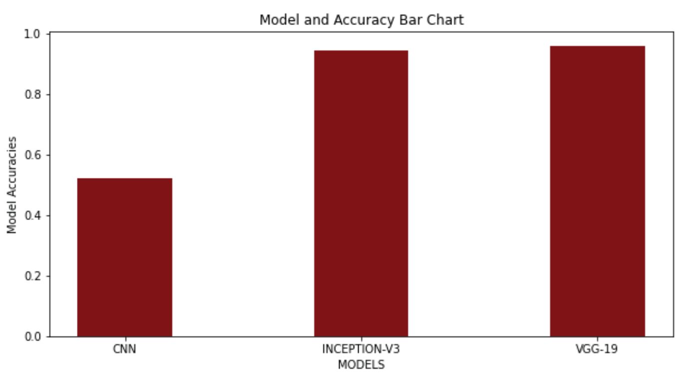

Fig. 4. Confusion Matrix

The confusion matrix for Inception V3 which was best performing model is as follows –

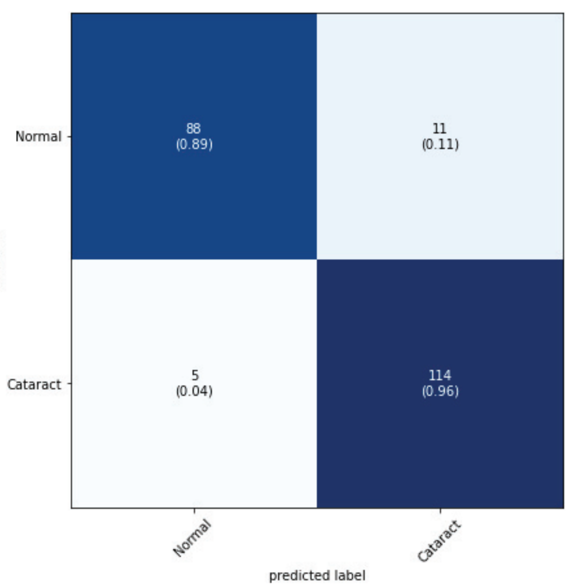

Fig. 5. Confusion Matrix

The confusion matrix for VGG-19 which was best performing model is as follows –

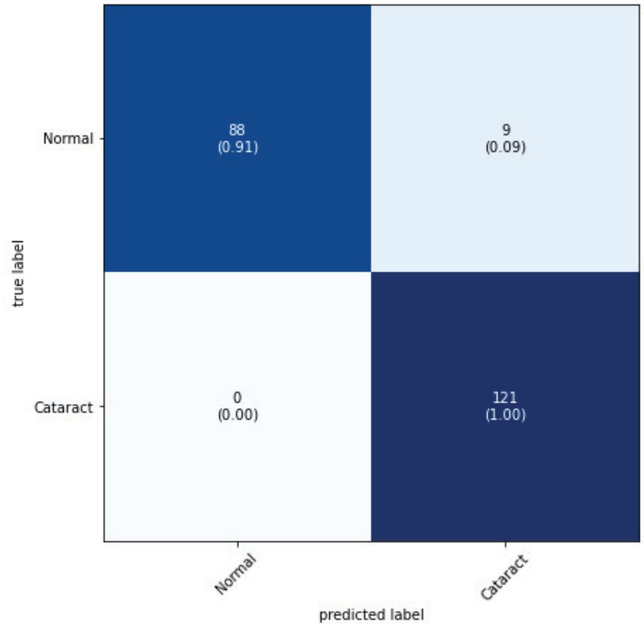

Fig. 6. Confusion Matrix

VGG-19 was the best performing model followed by Inception V3 and then CNN. There is a big gap between accuracies of CNN,VGG-19 and Inception V3. The reason behind it is the number of layers this model provides are far higher than custom CNN model.

This fig 7 represents the CNN Model's loss curve which is the best performing model.

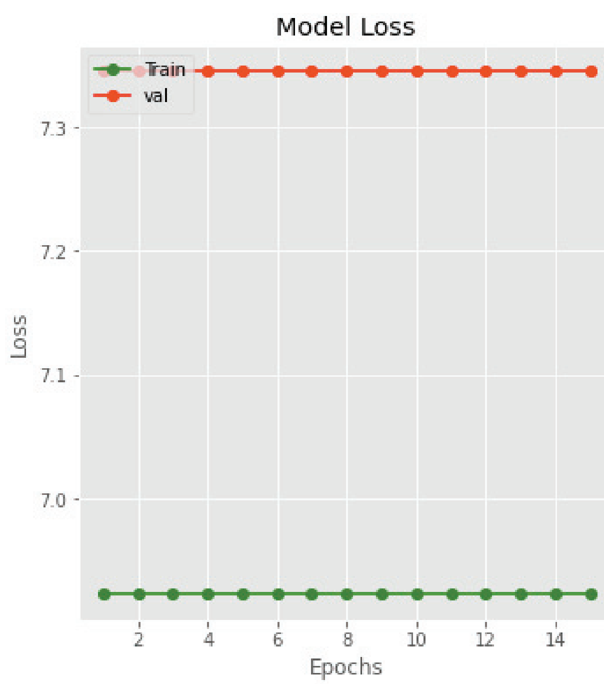

Fig. 7. Loss Curve

This fig 8 represents the CNN Model's accuracy curve which is the best performing model.

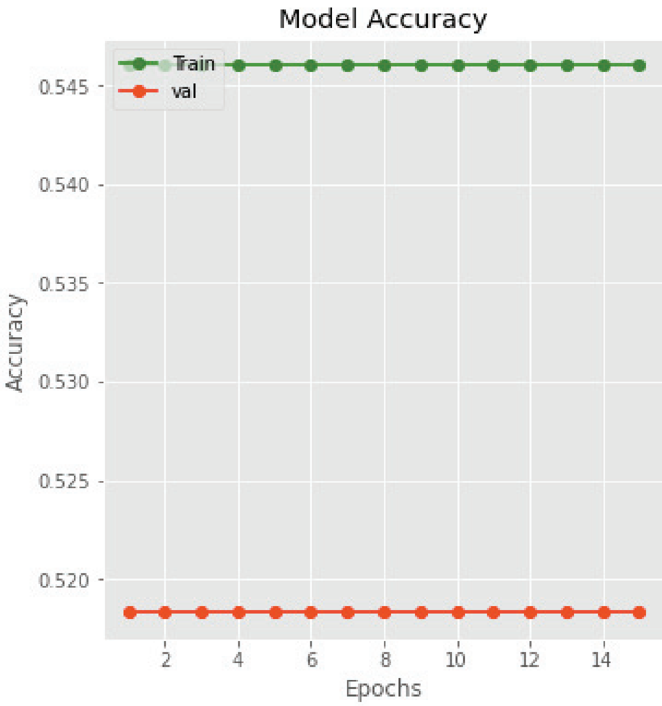

Fig. 8. Accuracy Curve

This fig 9 represents the Inception V3 loss curve which is the best performing model.

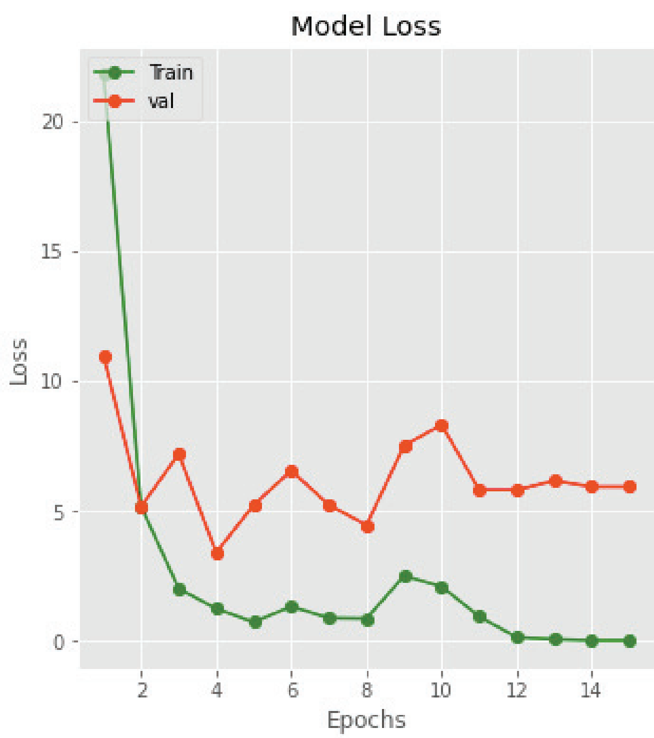

Fig. 9. Loss Curve

This fig 10 represents the Inception V3 Accuracy curve which is the best performing model.

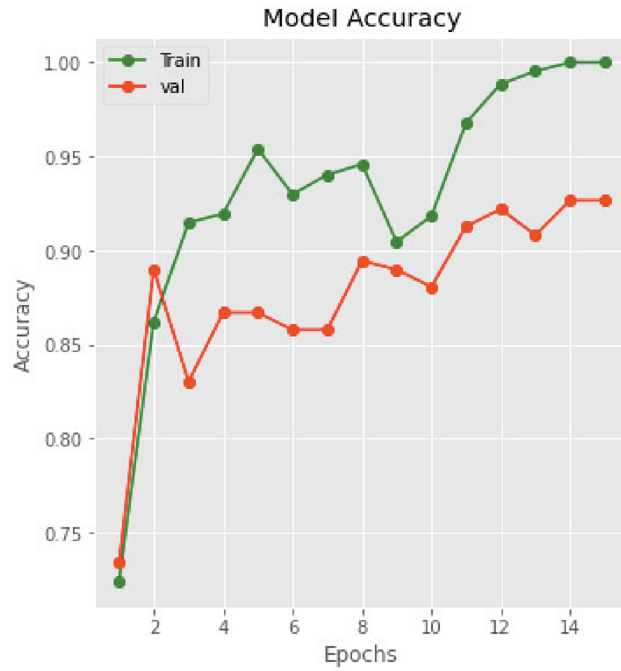

Fig. 10. Accuracy Curve

This fig 11 represents the VGG 19 Model's loss curve which is the best performing model.

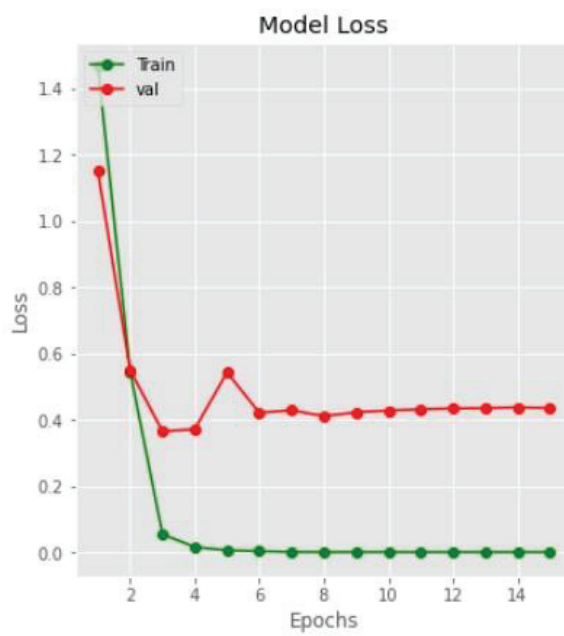

Fig. 11. Loss Curve

This fig 12 represents the VGG 19 Model's accuracy curve which is the best performing model.

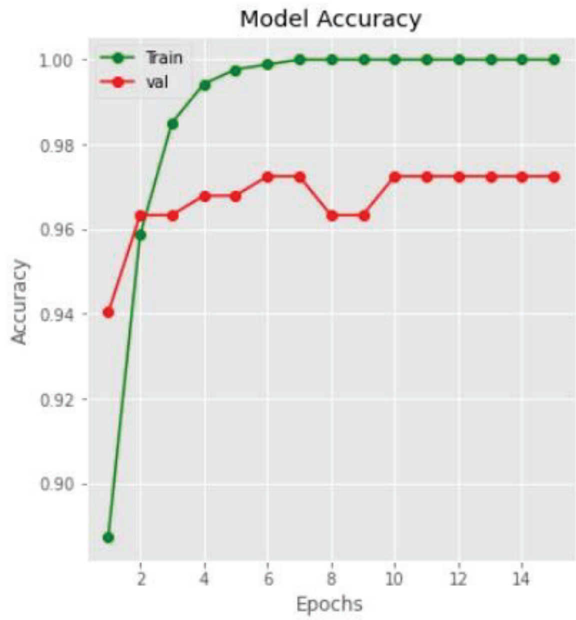

Fig. 12. Accuracy Curve

VGG16 neural network design is good. It is a straightforward stack of convolutional and max-pooling layers, each one coming before a final layer that is fully connected. In other words, it cannot extract features that are extremely complex. Inception nets, on the other hand, have inception modules that are made up of 1X1 filters, also referred to as point wise convolutions, followed by convolutional layers with various filter sizes applied concurrently. Inception nets can now learn more intricate characteristics

We can use VGG-19 and Inception V3 to solve complicated issues. In our instance, VGG-19 performs somewhat better than Inception V3.

We tested our model on testing dataset and we got the following results.

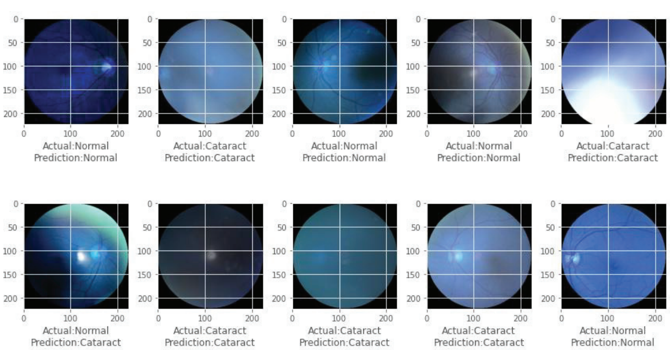

Fig. 13. Prediction Results

VII. SCOPE OF RESEARCH

Pattern recognition is used by ophthalmologists to diagnose problems by looking at the eye and its surrounding tissues directly or indirectly. This study focuses on the prediction of cataract illness, which is one of the ocular diseases.

VIII. LIMITATIONS AND FUTURE SCOPE

Deep Learning models require a large dataset to determine model accuracy. Dataset collectionon requires equipment that may not be available in local hospitals, and this would prevent data collection on a broader scale. Another restriction of this study is that any model must be thoroughly tested before being deployed for medical use, as the subject is extremely sensitive when dealing with people's lives.

As a future scope to this research, we aim to increase the model accuracy by collecting more data and improve the model architecture by ensembling techniques aiming to reduce the percentage of false negative errors in the model.

IX. CONCLUSIONS

Deep Learning approaches are unique ways for detecting and classifying distinct anomalies in eye pictures, and they have a lot of promise for diagnosing ocular diseases efficiently. Using these deep learning algorithms, decision making becomes powerful in field of ocular disease.

VGG-19 model stood out with the highest accuracy among different models. It is giving better accuracy as compared to CNN and Inception -V3. The creation of new models to show and extract characteristics that aid in the prognosis, diagnosis, and follow-up of ocular disorders is required for novel medical equipment utilization for detecting eye diseases. As a result, creating deep learning algorithms that incorporate multi-modal input is still difficult.

Despite the excellent findings, these methodologies face significant open difficulties in terms of interpretability and medical professional feedback to the models. Furthermore, the use of deep learning techniques in medical institutions has the potential to enhance the number of individuals diagnosed, resulting in an improvement in population quality of life. To fully realize the promise of these tools, engineers and ophthalmologists must collaborate in a coordinated, multidisciplinary effort centered on the patient in order to reduce medical diagnosis time and costs.

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