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Classification of Eye Disorders based on Deep Convolutional Neural Network

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Abstract: ***Multiple Eye Diseases are currently diagnosed visually by ophthalmologists. In the beginning period, the huge scope screening of eye diseases is outlandish since there are less number of ophthalmologists and in addition these strategies expend additional time. This indicates that in order to correctly identify the disease, manual intervention and the proper infrastructure is important. Owing to the fact that many developing nations are not able to provide their masses with the basic healthcare facilities, the need for computer-aided systems that are robust and inexpensive increases manifold. Over the last few years, convolutional neural networks (CNN) are being increasingly employed for the task of automatic and semi-automatic image classification. Through this paper, we aim to develop a method using deep learning architecture to detect eye disorders in fundus images. In the initial step preprocessing is accomplished for the fundus image, trailed by feature extraction and order. Different evaluations of influenced pictures are tried by the proposed technique and the presentation has been looked at and examined. The models would be tested using standard evaluation metrics to evaluate the effectiveness of the models.***

Keywords : Deep Learning, fundus image classification, convolutional neural networks, epoch.

I. INTRODUCTION

Most visual weaknesses are brought about by disease and ailing health. The first normal reasons for visual impairment are Cataract, Glaucoma and retinal disease. Cataract[1] remains the leading explanation for blindness consistent with the WHO, cataract is at risk for 51% of world visual deficiency, which speaks to around 20 million individuals (2010). As individuals inside the world live more, the quantity of people with cataract are foreseen to develop. A cataract is additionally a crucial explanation for low vision in both developed and developing countries. Glaucoma[2] is an eye disease which is known for centuries and people suffering from Glaucoma face difficulties for its early diagnosis. The number of persons who are blind because of glaucoma has been estimated to be 4.4 million, which resulted in little more than twelve percent of global blindness.

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Retinal diseases[3] are the foremost common explanation for childhood blindness worldwide. Around nine percent of the world's visual impairment originates from retinal infection. Some of these children are blinded by acquired retinal conditions, similar to retinitis pigmentosa, which may nor be dealt with nor forestalled at the present.

A. Data Acquisition

There are four types of datasets used for the present work. All the datasets are taken from Kaggle. The datasets are for: Cataract, Glaucoma, Retinal diseases and normal eyes. The dataset for normal eyes contains 300 images and the rest of the datasets contains 100 images each.

B. Preprocessing

Preprocessing[4] is done for converting the raw data into a clean data set. So, when the data is gathered from the data set, it may not be feasible for the analysis. We need to make sure that all images have the same range of values, i.e. histogram normalization, i.e. ensure that the base of the color histogram stretches from 0-255. The following things are done as a part of Preprocessing:

a) Histogram Normalization

Histogram normalization[5] is the most used technique to enhance smaller details within an image. Each section in the aggregate histogram is handled as the whole of all the picture intensity histogram esteems (checking that grey level), at that point it is scaled all together that a definitive worth is 1.0.

b) Gray Scaling

The pictures will be changed over to dim scale[6] (scope of gray pictures from white to dull) the framework will assign each pixel a worth upheld by how dim it is. All the numbers are set into a cluster after which the computer does calculations on the exhibit.

c) Binarization

Binarization[7] is employed once you want to convert a numerical feature vector into a Boolean vector. The threshold shall be properly chosen for binarizing the image. We obtained good results by setting the edge at 25% of the gray intensities contained in the image.

C. Data Preparation

The list of image files and corresponding labels are prepared following which images in the files are read and processed. The training and testing data are prepared for modeling. The ratio of the training and testing data is 7:3. For every image within the dataset for training the model, the subsequent images also are trained:

1. Brighter image
2. Deemer image

3. Flipped image (left-right)
4. Flipped image (up-down)
5. Brighter image of flipped image (left-right)
6. Brighter image of flipped image (up-down)
7. Deemer image of flipped image (left-right)
8. Deemer image of flipped image (up-down)

D. TRAINING MODEL

The neural network model which is used to train the data into is CNN (Convolutional neural network). Convolutional neural networks (CNN). CNN uses some of its features of the visual area and has therefore achieved state of the art results in computer vision tasks.

A typical CNN has nodes in one layer sparsely connected to nodes in the next layer which use the sliding scalar product, called convolution. To process the input data, a fully connected feed-forward neural network[8], as in NLP, when used for images, will not only classify the images but will automatically learn the features as well. However, it is impractical to use such a way for images as even a tiny image can produce tens of thousands of weights that require to be passed to each neuron in the subsequent layer. This number increases exponentially with each hidden layer. Convolution solves the matter by extracting and using small patches of the image rather than the whole image.

II. RELATED WORK

Any machine learning-based classification technique uses a multi-classification method so as to categorize the various sorts of eye disorders. Within the paper proposed by Huiqi Li and Hwee Ying Lim [9], SVM (Support Vector Machine) classifier is employed to 11grade nuclear cataract automatically. It works by checking out a multidimensional space that separates out classes.

Meindert Niemeijer [10] proposed an alternate order technique for identifying red sores in computerized shading fundus photos. Their methodology depends on the [11] which partitions the perceptions into various groups depending on the quantity of bunches should have been separated into. The accuracy achieved in this paper was 87%. which isn't probably the only one to use.

Retina vessel segmentation proposed by Jao V.B. Soares [12] uses 2-D Gabor wavelet and Bayesian classification to segment the vasculature in retinal images. Gabor filtering is fit for filtering the noise and enhancing the vessel during one stage. Bayesian classifiers with likelihood functions depicted as Gaussian mixtures, produces a quick classification while at the same time having the ability to demonstrate complex decision surfaces.

Hafsah Ahmad proposes a paper [13] for the detection of glaucoma using retinal fundus images which mainly affects the blind spot by increasing the cup size. They use a cup to disc ratio and the ratio of Neuroretinal Rim in inferior, superior, temporal and nasal quadrants for locating the diagnosis of glaucoma. It results in an accuracy of 97%.

Mehmet Emre Sertkaya proposed a paper [14] for the analysis of eye retinal diseases bolstered convolutional neural networks utilizing optical coherent images. During this method three designs of deep learning were utilized to be specific AlexNet, LeNet and Vgg16. In every architecture, the hyperparameters were changed to analyze these diseases. Aftereffects of the execution demonstrated that showed great results in Vgg16 and AlexNet architecture. The dropout layer structure in AlexNet has appeared to reduce the loss.

Meimei Yang proposed a paper [15] for the classification of retinal image for programmed cataract detection. The classifier utilized here is BP (Back Propagation) neural network which has two layers, supported by the clearness level of the retinal image. The patients' cataracts are ordered into normal, mild, medium or severe ones.

Huazhu Fu proposed a paper [16] for a disc-aware ensemble network for glaucoma screening from fundus images. During this technique, an absolutely extraordinary Disk-aware Ensemble Network (DENet) for customized glaucoma screening is proposed, which organizes the profound progressive setting of the general fundus image and along these lines the nearby blind spot region. The trials on two glaucoma datasets (SCES and new SINDI datasets) shows that the strategy beats other algorithms.

III. FINDINGS

Ref. No.	Dataset	Methodology	Merits	Demerits	Accuracy
[9]	SiMES	SVM Regression to classify the images	A large dataset is used for training the model.	The mean error for the grading system is higher.	97.0%
[10]	-	K-nearest neighbor classifier	Has a sensitivity o f 100%.	Abnormal images were not detected.	87%
[11]	STARE DRIVE (Publicly available)	2-D Gabor wavelet and supervised classification	Methods implemented are simple and efficient.	False detection of noise.	95.0%
[12]	DMED Dataset, FAU data library.	Extraction of optical disc and cup.	The average computational time is less than one second.	The training dataset is not large enough.	97.5%

[13]	OCT Dataset	Convolutional neural networks.	Dataset is large enough to train the model.	Loss reduction because of the use of the dropout layer in AlexNet.	93.0%
[14]	Retinal image database from patients.	2-Layer BP neural network.	Image quality is great after preprocessing for training the images.	Preprocessing time is more.	82.9%
[15]	SINDI Dataset	Disc-aware ensemble network	The data set is large enough.	Implementing is difficult.	83.2%
[17]	Madrid DRIVE	Stochastic watershed transformation.	Specificity and sensitivity results are high.	The training dataset is not large enough	87.1%
[18]	STARE DRIVE (Publicly available)	Simple line vectors	Simple to implement.	It has a huge number of non-vessel pixels.	94.5%
[19]	SiMES	Utilizing spoke like features to separate cortical opacity from other types	The success rate is very high ~ 98%	Detection is not robust.	85.6%

The analysis of the literature on the methods of eye disease classification using machine learning and deep learning led to various conclusions, which should be used in further works in the future. In terms of the pre-processing phase we can conclude that data augmentation definitely helps in increasing the training efficiency. Also datasets can be increased by using augmentation techniques like flipping, rotation and cropping instead of adding more images. which will obviously be time-consuming and complex. Another conclusion drawn is that the transfer learning approach to train the neural networks gives a high level of classification accuracy. From the papers discussed the best classifier used is SVM Classifier[20] according to our conclusion. Some of the techniques related to the proposed system have been discussed in detail in the next section.

IV. TECHNIQUES

A. SVM CLASSIFIER

The paper [21] is about detecting eye disorder using SVM Classifier with five fold validation. A Support vector machine develops a hyperplane or set of hyperplanes during a high-or endless dimensional space which might be utilized for characterization, relapse, or different errands like inconsistency recognition. Instinctively, a fair detachment is accomplished by the hyperplane that has the most significant separation to the nearest training data point of any class (so-called functional margin), since by and large the bigger the edge, the lower the speculation blunder of the classifier. Thermal pictures were utilized for preparing the data. Warm pictures were pre-prepared, by then Gray Level Cooccurrence Matrix (GLCM) based surface features from dim pictures, factual features from RGB and HSI pictures were isolated and gathered using classifiers with various mixes of highlights. A fivefold cross-approval plot is used to strengthen the speculation capacity of the proposed framework. Figure 1 delineates the design of the proposed framework. Trial results procured for various element blends give the best accuracy of 86. 23%, the affectability of 94. 08% and explicitness of 79.17% using SVM classifiers with five-overlap approval.

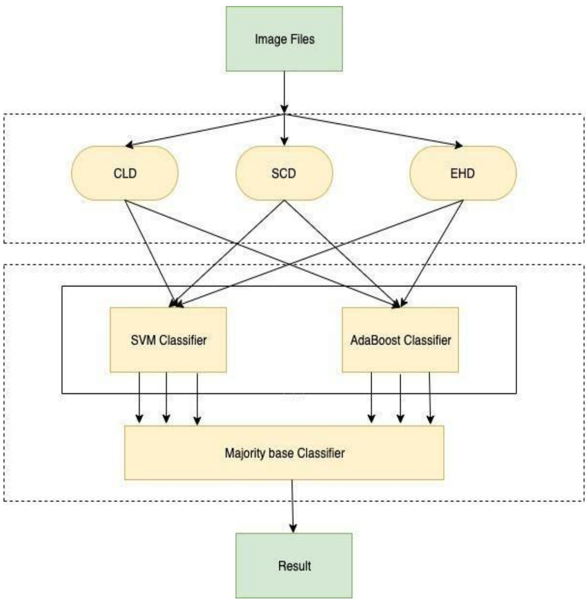

Figure 1. Architecture of a SVM Classifier

B. DECISION TREE

The paper [22] is about eye refractive error game plan which utilizes three AI procedures for foreseeing the seriousness of the consideration I.e., Naive Bayesian, SVM and J48 Decision Tree. AI Decision trees may be the preparation of choice trees supporting the given class-named preparing tuples.

An assurance tree is normally a progressive based tree structure, where each inner node (non-leaf node) signifies an assessment with quality, each branch demonstrates an end in the examination, and each leaf node conveys a class name. The highest node inside a tree may be the premise node. In the field of anticipating and grouping clinical examination issues, choice trees offer a powerful arrangement. Various choice tree calculations are applied to characterize genuine and counterfeit datasets, as C4.5, J48, ID3, C5, CHAID, and CART[3]. Each node for the choice tree is found by figuring the best data gain for all qualities. In the event that a chosen characteristic gives an unambiguous result, the part of this trait is ended and target esteem is allocated. Each characteristic inside the dataset is considered, by partitioning the information into a kind of little modules. It analyzes standardized data gain which contrasts in entropy that originates from picked attributes similar to a split point. The best standardization is utilized inside the highest point of the tree. The strategy is circled till the leaf node is created to the tree indicating class trait which is picked. In the outcomes acquired we can see J48 Decision tree has an extremely low blunder rate, and when contrasted with the other two usages, it accomplished a high precision. The computational time of Naïve Bayes is less because of the oversight of complex iterative estimations of the parameter and progressively it very well may be applied on an outsized dataset. Figure 2 delineates the engineering of the proposed framework. The preparation time of SVMs is exceptionally delayed notwithstanding having the ability to display complex non-direct choice limits.

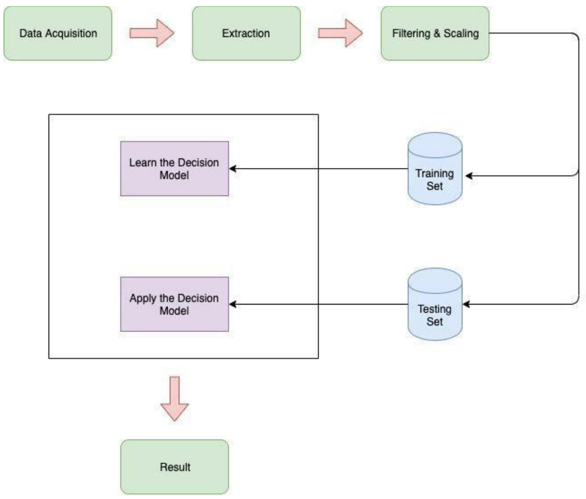

Figure 2. Architecture of the Decision Tree

C. Naive Bayesian

The paper [23] presents a specialist framework for diagnosing diseases that bolstered Naive Bayes. Naive Bayes might be a straightforward system for building classifiers: models that relegate class names to issue occurrences, spoken to as vectors of highlight esteems, where the classification names are drawn from some limited set. There isn't one calculation for preparing such classifiers, yet a group of calculations bolsters a standard rule: all Naive Bayes classifiers expect that the value of a particular element is free of the value of the other element, given the classification variable. The created master framework applies Case-Based Reasoning (CBR), which might be a worldview for thinking as a matter of fact while the Naïve Bayes is utilized as a route for grouping eye maladies by applying Bayes' hypothesis. The yields of the master framework are the grouping of eye fixed diseases and information on the least complex treatment. The aftereffects of this investigation are gotten by contrasting the master framework demonstrative outcomes and a specialist indicative outcome. upheld the test results, the Naïve Bayes based master framework has been prepared to get 82% exactness. Bolstered by the exploratory outcomes, it is regularly presumed that the blending of Case-Based Reasoning and Naïve Bayes inside the master framework shows a promising outcome. Figure 3 depicts the design of the proposed framework. Be that as it may, much work despite everything must be done before a full-size master framework is made with standard master frameworks segments.

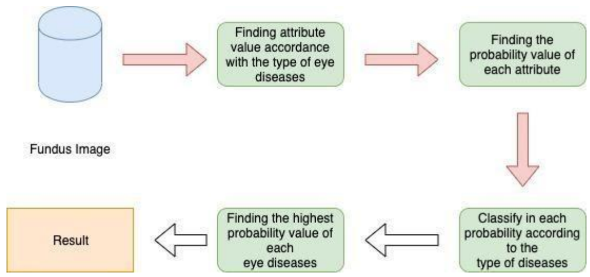

Figure 3. Architecture of the proposed Naive Bayesian

V. PROPOSED WORK

A. Motivation Of Algorithm

As manual mediation and certain equipment are necessary for the diagnosis of eye diseases and many developing nations are not able to provide their masses with the basic healthcare facilities, the need for computer-aided systems that are robust and inexpensive increases manifold. Through our project, we aim to develop an automatic screening tool which would be able to diagnose an image of a fundus as normal or cataract affected or glaucoma affected or retina disease affected with reliable accuracy. By using the current state-of-the-art architectures of deep learning models, multi-class classifiers such as convolutional neural networks it would be possible to build a model that would have the ability to classify previously unseen data into malignant or benign categories. Using the recent developments in the technique of transfer learning, the project would use renowned robust architectures, previously trained on larger datasets, which would then be fine-tuned to work with classifiers for our fundus images.

B. Architecture

In the proposed system four sorts of datasets are used. Figure 4 depicts the architecture of the proposed system. The datasets are for: Cataract, Glaucoma, Retinal disease and Normal eyes. Initially, preprocessing is completed for converting the data into a clean data set. Histogram Normalization (used to reinforce fine detail within an image), Gray Scaling (images are converted to gray scale (range of gray shades from white to black) the pc will assign each pixel a worth supported how dark it is), Binarization (used to convert a numerical feature vector into a boolean vector). The pre-processed data is then segregated into training data and testing data.

The training data is employed to coach the model that is chosen, here CNN model is trained. the subsequent layers are used for training the model:

1. One Input Layer.
2. Three Convolutional Layers.
3. Three Max Pooling Layer.
4. One Dropout Layer.
5. One Flatten Layer.
6. Three Dense Layer.
7. One Output Layer.

Model is about arbitrary weights. At the top model will spit out the output for a given input. It computes the loss/error of the output by watching what the model predicted for the input versus what the model's true label is. It also computes the gradient of the loss function w.r.t each of the weights then the gradient is multiplied with a learning rate(0.01-0.0001). the load is updated by ditching the previous weight. the load reaches closer to their optimised values while SGD(Stochastic Gradient Descent)[24] works to minimise the loss function. By using the "batch size" concept the info is trained within the sort of batches. Larger the dimensions of the batch, faster the training time, lower the standard of the model. Also, the concept of "epochs"[25] keeps count of the number of times a group of knowledge is trained. For batch training all of the training samples undergo the training algorithm simultaneously in one epoch before weights are updated.

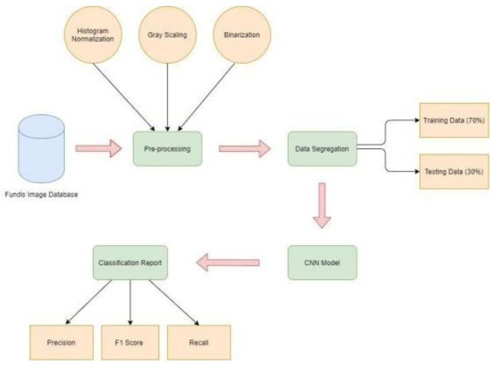

Figure 4. The architecture of the proposed system

C. EXPERIMENTAL RESULTS

The training set contains a random selection of 70% images from the whole dataset and the remaining 30% are used for testing. Figure 5 shows the progression in accuracy while training the model. For each image in the training set the image is flipped, brightened, dimmed versions are also trained. We used a framework based on CNN which was able to give the accuracy measure of 85%.

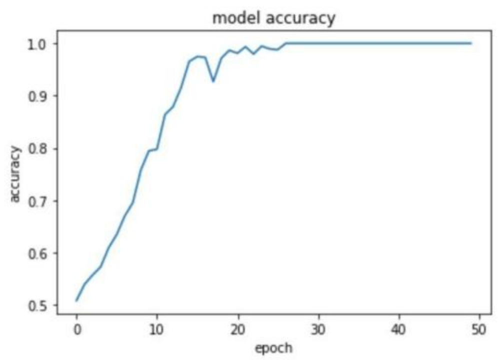

Figure 5. Model Accuracy

VI. CONCLUSION

The use of a framework based on Convolutional Neural Network to detect eye diseases helped to utilise the Dropout and Max Pooling Layers available in CNN for getting better efficiency in the proposed work. The accuracy was found to be 85% which is good enough in terms of CNN results. Data Augmentation helped in improving the dataset and the NN model created with the number of layers (as explained in section V(B)) was perfectly fir for the classification whilch led to gain better accuracy and hence improving the accuracy. This project would mark the first step in an effort to increase the accessibility of medical utilities in the backward and rural areas. If detected early, there is a high recovery chance for thousands of patients who would benefit from our project. Further enhancements of this project could be deployed across multiple health care facilities not only as screening tools, but also as safety-net expert systems.

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