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Glaucoma Prediction Using Deep Convolutional Neural Network

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Abstract

Pressure of the fluid intraocular damages the optical nerve of eye and this disorder is known as Glaucoma eye disease. Pressure will be generated due to increase in eye fluid. It is observed that 4.5 million people are suffering from Glaucoma every year globally. More than 12% of the people among all blindness are because of glaucoma. Glaucoma is globe's second most commonly observed reason of blindness. This type of eye disease is found in the people with age of above 40 years. In this application deep convolutional neural network (DCNN) is used for prediction of glaucoma disease from retinal fundus images. There are many machine learning algorithms have been implemented by different researchers which has lower accuracy and performance. To get improved performance deep learning algorithm has been used with a greater number of epochs and a greater number of layers. LAG dataset is used which is collected from Kaggle.com website. This dataset contains two categories' data such as 'Normal' and 'Glaucoma'. Performance is calculated using accuracy, precision, recall and F-score. Confusion matrix also plotted for both SVM classifier and deep CNN classifier which represents plot of predicted class of glaucoma image by given algorithm versus actual or true class of glaucoma image present in dataset. As proposed deep CNN classifier has superior performance in all the metrics over SVM classifier for prediction of glaucoma in retinal fundus image so for further testing the deep CNN classifier is recommended for both users and ophthalmologists. In future, security and new features like internet of things (IoT) can be added to the proposed classifier results to get additional security and easy handling of data by ophthalmologists using IOT.

Keywords: Deep CNN (Deep Convolutional Neural Network), Glaucoma Detection, Deep Learning, Machine Learning.

I. INTRODUCTION

In this work, a novel glaucoma detection algorithm based on wavelet transforms is introduced, utilizing both statistical and textural features. The wavelet transforms, known for its multiresolution localization and capability in both frequency and time, is key to the algorithm. By decomposing images into detail and approximation sub bands, the algorithm focuses on the approximation sub bands, which contain valuable illumination and textural information relevant to glaucoma detection. The optic disc region is initially detected from the red channel's approximation sub band, followed by the extraction of statistical and textural features from the green and blue sub bands. Feature selection refines these features for effective classification of retinal images from two public datasets, differentiating between healthy and glaucomatous eyes. [1]

Face detection is a complex and ongoing area of research, primarily focused on developing algorithms that can accurately recognize faces in images, even under varying conditions such as illumination, orientation, and scale. Traditional approaches to face detection have utilized methods like template matching, knowledge-based techniques, and appearance-based algorithms, including machine learning, neural networks, and

PCA. In this study, the preprocessing step involves converting the input image into patches, removing noise, and selecting patches above a certain threshold. Finally, the extracted features are classified with an ANFIS classifier, with the output further optimized using the Artificial Bee Colony (ABC) algorithm. [2]

This paper introduces a novel method for detecting glaucoma using digital fundus images. The process begins with preprocessing the eye fundus images, followed by feature extraction using Principal Component Analysis (PCA). The extracted features are then used to train a SVM classifier. The performance of the classifier is evaluated through cross-validation, allowing it to effectively distinguish between normal and glaucoma-affected eye fundus images with a certain level of accuracy. [3]

The literature highlights several drawbacks in existing glaucoma detection studies: inconsistent use of structural and non-structural features, lack of appropriate feature selection methods, varying classifiers, and inconsistent datasets. To address these issues, this study proposes using both non-structural and structural features for classification, employing five different feature selection methods to rank and create a reduced, significant feature set. We then classify normal and abnormal retinal images using a novel combined feature set. We compare the effectiveness of different classifiers, conducting all experiments on the same dataset to ensure unbiased results. This study aims to improve classification accuracy by using both structural and non-structural features. It employs five distinct feature selection methods to rank and reduce the feature set, resulting in a novel, optimized set of features for classifying abnormal and normal retinal images. We test multiple classifiers to determine the most effective one for the task. [4]

Many efforts have been made to develop systems for early glaucoma detection using deep learning algorithms, as early detection can prevent blindness. This study proposes using a Convolutional Neural Network (CNN) to classify and differentiate patterns in retinal images, helping to identify glaucoma. The CNN model, consisting of six layers, incorporates a dropout mechanism to enhance performance, aiming to accurately distinguish between normal and glaucoma-affected eyes. [5]

This research primarily focuses on diagnosing glaucoma by analysing retinal fundus images. We developed a computer-aided detection (CAD) system as a desktop application to help healthcare practitioners automatically classify and screen images as either healthy or glaucomatous. The method leverages deep learning models like neural networks, U-Net, and LeNet operating entirely offline, making it accessible for clinicians in rural areas. The system simplifies the typically time-consuming glaucoma diagnosis process by using three key features blood vessels, ISNT ratio, and CDR as decision criteria. A majority voting system, employing adaboosting, NN, and SVM classifiers, enhances classification. The research also advances glaucoma detection by training on diverse datasets, increasing the number of classifiers for better generalization, and ensuring the significance of features used in classification. [6]

II. LITERATURE SURVEY

We propose a wavelet-based glaucoma detection algorithm for real-time screening to facilitate early diagnosis and lessen the strain on ophthalmologists. This method uses textural and statistical features derived from the optic disc region of retinal images to distinguish between healthy and glaucomatous eyes. Tested on two public datasets of varying resolutions, the algorithm achieved an accuracy of

96.7% and an AUC of 94.7% on the high-resolution dataset. [1]

This paper presents an efficient face recognition method that combines ANFIS-ABC and Adaptive Genetic Algorithm (AGA). The process begins with the pre-processing of face images from the database. In the second stage, an interest point is determined to enhance the detection rate, with its parameters optimized using AGA. The final stage involves classifying face images using ANFIS, where the parameters are further optimized using the Artificial Bee Colony (ABC) algorithm to boost accuracy. The proposed ANFIS-ABC technique is evaluated using the real-time video, YALE-B database (165 images from 15 individuals), and ORL database (400 images from 40 individuals). The false alarm rate and detection rate are compared with existing methods to demonstrate the system's efficiency. [2]

Increased intraocular pressure frequently causes glaucoma, a leading cause of blindness worldwide known as the Silent Thief of Sight. Traditional detection methods like Heidelberg retinal tomography (HRT) and optical coherence tomography (OCT) are expensive. This paper proposes a cost-effective method to diagnose glaucoma using digital fundus images. The approach involves image pre-processing, feature extraction using PCA, and classification with SVM. MATLAB implements these techniques to effectively analyze and differentiate between glaucomatous and normal eyes. [3]

Traditional diagnostic methods like pachymetry and tonometry are require human interaction, time-consuming, and are prone to subjective errors. To address these challenges, this paper explores the use of computer-aided diagnosis (CAD) and medical imaging systems to classify retinal images as abnormal or normal using machine learning. The proposed method combines structural features, such as Disc Damage Likelihood Scale (DDLS) and Cup to Disc Ratio (CDR), with non-structural features like wavelets, HOC, HOS, FoS, GLCM, and GLRM. The study also presents a comparative analysis of classifiers, including Naïve Bayes, SVM, Random Forest, Neural Network, and k-NN, evaluated using precision, specificity, accuracy, and sensitivity metrics. [4]

Glaucoma is an irreversible eye disease that leads to vision deterioration. To improve detection, this paper proposes a deep learning architecture using Convolutional Neural Networks (CNN) for accurate glaucoma identification. The CNN differentiates between non-glaucomatous and glaucomatous patterns by providing a hierarchical image structure. The proposed method, evaluated using six layers and a dropout mechanism, was tested on the ORIGA and SCES datasets, achieving accuracy values of 0.822 and 0.882, respectively. [5]

Increased intraocular pressure in the retina causes glaucoma, a neurodegenerative eye disease that can potentially lead to blindness if not diagnosed early. As the second leading cause of blindness globally, there is a critical need for a system that can diagnose glaucoma effectively without relying heavily on specialized equipment or skilled medical professionals, and that is time-efficient. This study proposes an offline CAD system for glaucoma detection using retinal fundus images. The system incorporates machine learning, deep learning, and image processing techniques. We use the Le-Net architecture to validate input images and apply the brightest spot algorithm for region of interest (ROI) detection. The U-Net architecture manages the segmentation of the optic cup and optic disc, and employs Adaboost, Neural Network, and SVM classifiers for classification. Using Le-Net, the proposed system achieved 99% accuracy in input image validation. Classification using Adaboost, Neural Network, and SVM achieved a perfect accuracy, recall, specificity, and sensitivity of 100%, demonstrating the system's reliability. The developed CAD system is user-friendly and can significantly aid in early glaucoma detection. Its modular design allows for various tasks related to glaucoma detection and classification. Trained on diverse datasets, the system is robust and highly accurate, making it a promising tool for early diagnosis. [6]

III. PROPOSED METHOD

Prediction of glaucoma from retinal fundus image is an important task and need precise results. As wrong results may get patient a wrong treatment. Proposed method used deep CNN architecture for prediction of glaucoma from retinal fundus images. In this there is comparative analysis of state of art machine learning technique as SVM and proposed new classifier deep CNN are used. For performance calculation multiple metrics such as confusion matrix, precision, accuracy, recall and Fscore are calculated.

Deep CNN classifier

Proposed deep CNN classifier contains sequential layers as mentioned below ,

a) Convolution layer
b) Max-pooling layer
c) Convolution layer
d) Max-pooling layer
e) Convolution layer
f) Max-pooling layer
g) Convolution layer
h) Max-pooling layer
i) Flatten Layer
j) Dense Layer
k) Dropout Layer
l) Dense Layer
m) Dropout Layer
n) Dense Layer

Convolution layer contains different filters to obtain relevant features from input data. Padding and strides are the important components of convolution layer. Max-pooling is used to reduce data complexity by selecting relevant features and removing unwanted features from input data of convolution layer. Flatten layer is used for conversion to one dimensional feature vector from multi-dimensional feature vector. Dense layer are used prediction of the features from different class. Dropout layer is used to overcome the drawback of overfitting.

Proposed method used has several steps as shown in below figure,

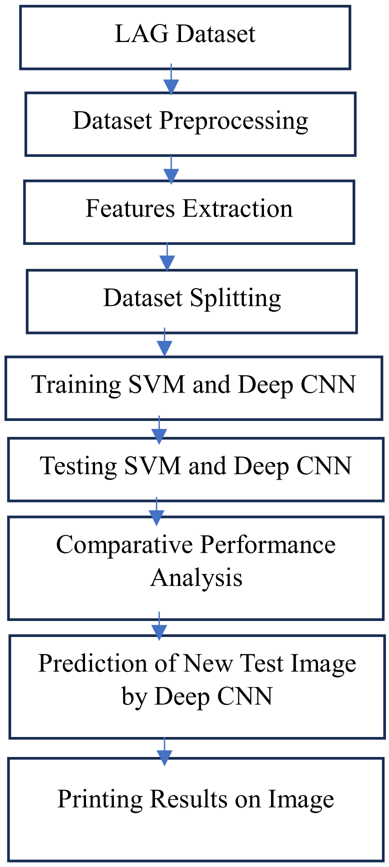

Fig. Block diagram of proposed method

Proposed method block diagram steps are discussed in detail below,

Step1: Dataset Selection

In this application dataset is selected from Kaggle.com and the name of dataset is LAG dataset. The dataset contains 4854 retinal fundus images which has two classes as ‘Glaucoma’ and ‘Normal’. ‘Glaucoma’ folder contains all glaucoma retinal fundus images and having image count of 1711 and ‘Normal’ folder contains normal retinal fundus images and having image count of 3143.

Step2 : Dataset Preprocessing

In dataset preprocessing, images are obtained in standard format using resizing and normalization. All images are resized to standard size of 64x64. After resizing images are normalized to get pixel range from 0 to 1. After these preprocessing techniques images are obtained in standard format for further processing.

Step 3: Feature Extraction

Obtained images from preprocessing are further given for feature extraction to extract both histogram-based features and texture features. Both features are combined to get a single feature vector.

Step4 : Dataset features Splitting

In this step the feature vectors obtained are saved in X variable while their respective labels are saved in Y variable. Then using splitting function from python dataset features and labels are splitted into training set and testing set. In this application test set is chosen of size 20% while remaining 80% data is used for training both SVM classifier and deep CNN classifier.

Step5: Training SVM and Deep CNN

The obtained features from both sets of data is trained to SVM classifier which is state of art technique as well as proposed deep CNN classifier. The data for training is selected 80% among the whole dataset. After training the weights are saved in specific folder.

Step6: Testing SVM and Deep CNN

Weights obtained by training are further used for the remaining 20% data testing. Both SVM and deep CNN are tested on test data and the obtained results are used to compare with actual class labels of 20% data.

Step7 : Comparative Performance Analysis

The obtained class predicted results are compared with actual class labels of 20% data using different metrics such as confusing matrix, precision, accuracy, Fscore and recall. It is observed that deep CNN has better performance for all the above metrics compared with state of art SVM classifier.

Step8: Prediction on new test retinal fundus image data

As the deep CNN classifier has better performance over SVM classifier. So for further prediction weights of deep CNN classifier on new test retinal fundus images.

Step9: printing obtained results

The obtained class for prediction by deep CNN classifier on new test retinal fundus image is printed on image. Even obtained result is displayed on GUI screen.

IV. RESULTS ANALYSIS

Proposed method deep CNN for glaucoma prediction is compared with state of art SVM (Support Vector Machine) classifier. The results comparative analysis is performed using python on LAG dataset with different python libraries related to machine learning, deep learning, computer vision, etc. GUI (Graphical user interface) is prepared for displaying results in effective manner for users.

Fig: Graphical User Interface

This is the user interface prepared using tkinter library from python for displaying results in more interactive way with users. Different components used in the GUI are buttons, text, Label, etc.

Complete scenario of the comparative analysis between SVM and Deep CNN for glaucoma detection is performed using above GUI.

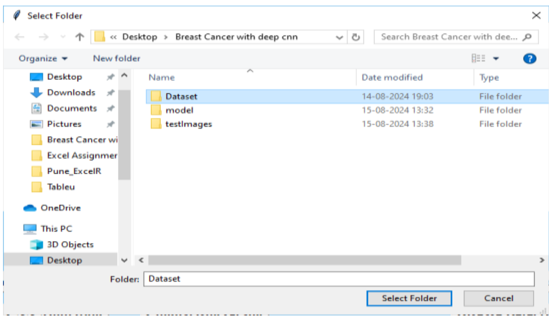

Fig: Uploading the dataset by user

User can select the dataset on which he wants to operate. The dataset used in this application is downloaded from Kaggle website named as 'LAG DATASET', which has two categories of data as 'glaucoma' and 'Normal'. The uploaded dataset by user undergoes training and testing in next steps.

Different Labels Found in Dataset : ['glaucoma', 'normal']

Total labels in the dataset are : 2

Fig: Displaying labels available in Dataset

After Uploading dataset, it will display number of labels found in dataset. Each folder will be opened checked for number of files present in the specific folder. Whole dataset is then splitted for training set and test set.

Total images found in dataset : 4854

Dataset train & test split. 80% dataset images used for training and 20% for testing

80% training images : 3883

20% testing images : 971

Fig: Dataset Splitting

After Loading the dataset, feature extraction is done and features data is splitted into 80% training and 20% testing. There is total 4854 images in main dataset including both category data as normal and glaucoma data. For training 80% of the data is used which contains 3883 images while testing 20% images are used which contains 971 images.

SVM Accuracy : 87.74459320288362
SVM Precision : 86.87460644570382
SVM Recall : 85.98170646557743
SVM FScore : 86.39327370893953

Fig. Performance metrics of SVM classifier

SVM performance metrics are displayed in above figure. It is observed that there are total four metrics has been used as accuracy, precision, recall and F-Score. The above metric results are obtained by comparison of predicted labels by SVM classifier and actual labels of images. Below there is confusion matrix which represent results in more effective way.

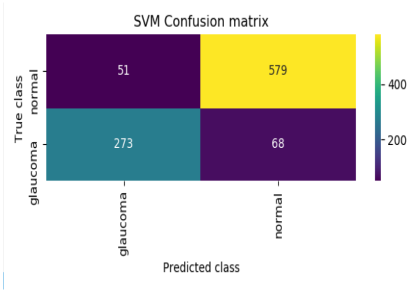

Fig. Confusion matrix of SVM classifier

SVM classifier used in this application is plotted in above figure which contains predicted class on X-axis and on Y-axis true class of the test images is shown. It is shown in above confusion matrix that 51 images are wrongly predicted while 68 images from test image data are wrongly predicted.

Training the SVM algorithm gives 87% accuracy. Confusion matrix shows the glaucoma and normal class prediction.

Proposed Deep CNN Accuracy : 99.48506694129763
Proposed Deep CNN Precision : 99.47143094657504
Proposed Deep CNN Recall : 99.40845187358167
Proposed Deep CNN FScore : 99.43980661501273

Fig. Performance metrics of Deep CNN classifier

Performance metrics of deep CNN for glaucoma prediction are calculated such as accuracy, precision, recall and Fscore. All the above metrics shows that value is very high means the correct prediction is more in deep CNN compared to SVM classifier.

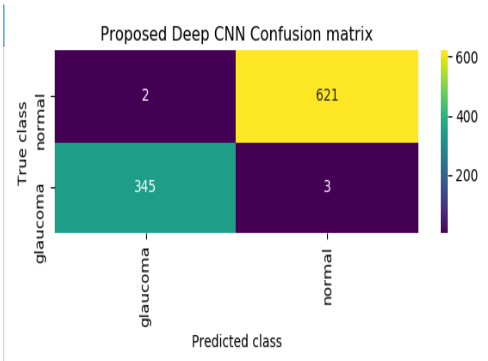

Fig: Proposed Deep CNN Algorithm

Deep CNN methods confusion matrix is shown in above figure. It is observed from above matrix that only 2 images normal image class are wrongly predicted while 3 images from glaucoma class are wrongly predicted that means the correct prediction is very high for deep CNN compared to state of art SVM classifier. Comparative performance is plotted in below graphs.

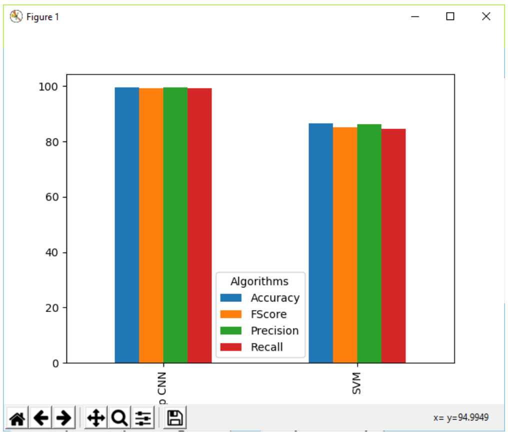

Fig: Comparison Bar graph of SVM and Deep CNN classifier

This is comparison bar graph of both SVM and deep CNN algorithm Accuracy, Precision, Recall and Fscore. In the bar graph, SVM classifier has lower performance of each metric than deep CNN

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classifier. As the deep CNN has higher accuracy and other performance metric value is high , deep CNN is preferred to ophthalmologist for further testing of images over state of art machine learning classifiers.

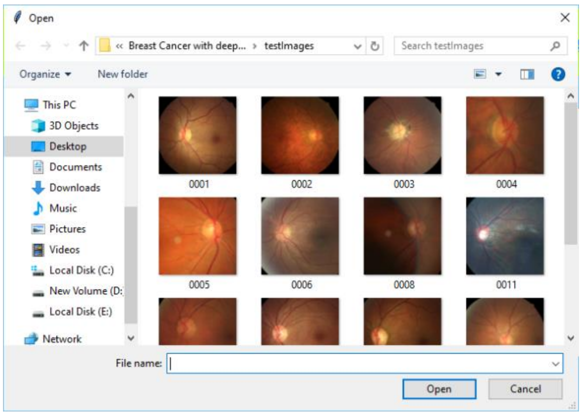

Fig: Prediction results of the new test images

Here from user image is selected for further glaucoma prediction. The selected image undergoes all the preprocessing steps and will be tested by deep CNN classifier.

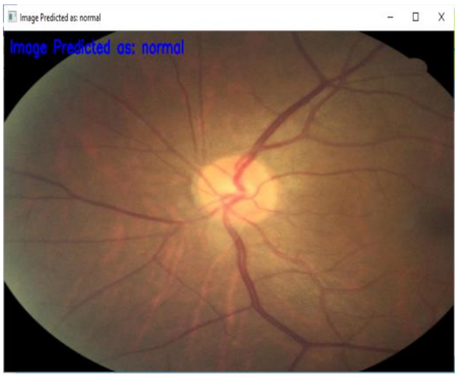

Fig: Predicted Result by Deep CNN classifier

Above image is predicted as normal image by proposed deep CNN classifier. As there is better performance of deep CNN over SVM classifier, Deep CNN is used for further prediction on new test data uploaded by users.

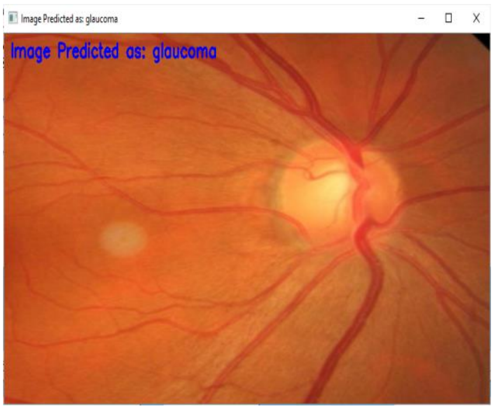

Fig: Predicted Result by Deep CNN classifier

Above image is predicted as glaucoma image by deep CNN classifier. As prediction accuracy is higher for deep CNN, for further testing deep CNN is used. Such any other retinal fundus image can be uploaded to the proposed model GUI to get results of glaucoma or no.

CONCLUSION

Proposed deep learning algorithm, deep CNN is successfully designed and analyzed on LAG dataset. Proposed algorithm is having superior performance compare to the state of art machine learning algorithms. Proposed algorithm is compared with existing machine learning algorithm using metrics such as precision , recall , F-Score and accuracy. In this application existing algorithm used is SVM (Support Vector Machine). Confusion matrix plot represents the predicted class of retinal fundus image versus actual class of retinal fundus image. For both SVM classifier and deep CNN classifier confusion matrix is shown to get understanding of performance of each classifier. The GUI prepared for proposed method is very user friendly so that user can easily upload any picture he/she wants to test, our proposed model identify class with very higher accuracy.

In this application GUI is prepared to analyze and predict the results but in future android app or website can be prepared to give easy access to the doctors or medical staffs. Even the predicted results can be integrated with internet of things (IOT) to get more interactive results for early prediction by saving lot of time required for the process of retinal fundus images.

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