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Squint Eye Disease Detection Using Machine Learning

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Abstract: *Eye plays an important role in human life. Squint eye is one of the eye diseases. It stands for crossed eye i.e., a condition in which the eyes do not align properly. "Squint eye disease detection using machine learning"- it aims to provide screening method for people who live in remote areas with poor medical accessibility. This model detects the type and percentage of the defect by uploading an image in a website, where types include esotropia, exotropia, hypotropia, hypertropia. Dataset is trained using CNN (convolution neural network) algorithm and this model is used to detect. Accuracy of the type is calculated using this model. Web application is developed using flask framework and detected result with details are displayed.*

Keywords: *Squint eye disease detection, convolutional neural networks, machine learning.*

I. INTRODUCTION

In recent years, eye detection has become an important research topic in computer vision and pattern recognition, because the human eye's locations are essential information for many applications, including psychological analysis, facial expression recognition, auxiliary driving, and medical diagnosis. However, eye detection is quite challenging in many practical applications.

The cameras are sensitive to light variations and the shooting distance, which makes the human eyes very eccentric in a facial image. Sometimes the face is partially occluded and we are not able to obtain a complete facial image. For example, half of the face was covered in a cover test for detecting squint eyes[1].

In this case, some existing eye detection methods do not work, because they rely on a facial model detection to locate the eyes. An eye detector is also expected to work well in various image modalities, that is, infrared and visible images. Moreover, the eye detection algorithm should be fast because it is supposed to be online in many practical cases.

Although many methods have been proposed to detect the eyes from facial images, we are attempting to develop an efficient and robust eye detection algorithm to fulfil the requirements of the applications as much as possible. The rest of this paper is organized as follows. In the Related Work, a review of related works is presented.

Most of the existing works present recognition results on one or two eye diseases, but there is still a lack of research on recognition of some other important eye diseases. The main pitfall in this area are the lack of benchmarks and lack of publicly available visual content-based eye disease datasets for many diseases. In this paper, we aim to develop a standard dataset with many samples as well as squint eye diseases.

We develop our dataset with four diseases and compares with normal eyes and the dataset contains multiple images. These datasets can be made available free of cost to researchers of other institutions. We develop our system for recognition of four eye diseases using CNN because, in general, CNN perform other machine learning techniques for many recognition tasks. The proposed method segments the facial components using a digital image processing technique.

Then, we detect the eye region automatically and these features are applied to CNN models. We also apply convolution neural network for feature selection and then classification is done using CNN based on the convolution output layer function. In this paper we choose four eye diseases including esotropia, exotropia, hypotropia, hypertropia. From the experimental results, we obtain 98.79% average accuracy with sensitivity of 97% and specificity of 99% by the proposed CNN model for four diseases [2].

Machine learning algorithms have been used for several challenging tasks, such as brain tumour segmentation with magnetic resonance (MR) imaging, age-related eye diseases, eye tumour detection, skin disease detection, and automated diabetic retinopathy testing.

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Digital image processing and machine learning techniques are also being applied in eye disease recognition. It may potentially be able to detect abnormal changes in the cells, sclera, cornea, iris, pupil, and blood vessels. Many eye diseases such as cataracts, trachoma, corneal ulcer, conjunctivitis, and ectropion can be detected by observing visual symptoms.

In the Method, we proposed an efficient method for eye detection, which consists of candidate region generation, eye region determination and classification, and eye centre positioning. Then, the training scheme, evaluation results, and discussions were presented in the Training Scheme, Evaluation, and Further Discussion, respectively.

Finally, conclusion remarks were drawn in the last section. Eye diseases can lead to partial or even complete absence of vision if they are left unobserved in the initial period. Early detection of these eye diseases can prevent vision impairment. In recent years, digital image processing and machine learning techniques are widely used for automatic disease detection, diagnosis, and clinical decision-making procedures to achieve the optimum and most accurate results [3].

Most people delay to take the correct steps to restore their eye disease problems. Expert eye doctors are able to identify diseases by observing eyes' visual symptoms but they are not available in many remote areas worldwide. Thus, researchers are interested in developing an automated intelligent system that can provide detection and segmentation of the eye region and classification of eye diseases.

Deep learning health practices constitute a multidisciplinary field of study. Although computer image classification is now inevitably included in our daily lives, it requires the interpretation of software with health applications by expert healthcare professionals [4]. Today, when the state of the technology, data processing speed and data processing capacity are taken into account, disease diagnosis with image processing stands as a hot topic in front of many researches in academia and private sector researchers

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CAUSES OF SQUINT

Most strabismus results from an abnormality of the neuromuscular control of eye movement. Our understanding of these control centres in the brain is still evolving. Less commonly, there is a problem with the actual eye muscle. Strabismus is often inherited, with about 30 percent of children with strabismus having a family member with a similar problem. Other conditions associated with strabismus include:

- Uncorrected refractive errors
- Poor vision in one eye
- Cerebral palsy
- Down syndrome (20-60% of these patients are affected)
- Hydrocephalus (a congenital disease that results in a build-up of fluid in the brain)
- Brain tumors
- Stroke (the leading cause of strabismus in adults)

II. LITERATURE SURVEY

Many algorithms have been proposed for image-based eye detection. These can be summarized into two categories, namely, traditional eye detectors and machine learning eye detectors. Traditional eye detectors are typically designed according to the geometric characteristics of the eye. These eye detectors can be divided into two subclasses. The first subclass is the geometric model.

Valenti and Gevers [5] used the curvature of isopods to design a voting system for eye and pupil localization.

Araujo et al. [6] described an Inner Product Detector for eye localization based on correlation filters. The traditional eye detectors sometimes can achieve good results, but they easily fail when there is a change in the external light or face occlusion.

Machine learning eye detectors can also be further divided into two subclasses. The first subclass is the traditional feature extraction followed by a cascaded classifier.. Chen and Liu [7] applied the Haar wavelet and support vector machine (SVM) for fast classification. Sharma and Savakis [8] proposed learning histogram of oriented gradients (HOG) features in combination with SVM classifiers to obtain an efficient eye detector. Leo et al. [9] used self-similarity information combined with shape analysis for eye center detection. A constraint based on the geometrical characteristics and neural

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classifier to detect the eye regions were proposed in [9].

Gou et al. [10] built a cascade regression framework for simultaneous eye localization and eye state estimation.

Kim et al. [11] proposed generating eye candidate regions by using multiscale iris shape features and then verifying those candidate regions using the HOG and cell mean intensity features. With the popularity of deep learning algorithms [17], some researchers used the convolution neural network to train eye detectors, which forms the second subclass.

Chinsatit and Saitoh [present a CNN-based pupil center detection method. In Fuhl's research, coarse to fine pupil position identification was carried out using two similar convolutional neural networks and the authors proposed subregions from a downscaled input image to decrease computational costs.

Amos et al. trained a facial landmark detector using 68 feature points to describe the face model in which 12 feature points described the eye contour. The deep learning-based methods have shown high robustness and detection accuracy compared with traditional methods.

However, the efficiency is still an issue. The facial images are usually larger than. This requires a large amount of computer resources if the CNNs have to perform a global search of the image. A quick and effective method is necessary to propose candidate regions such that only the selected candidate regions are fed into the CNN

III. PROPOSED METHODOLOGY

We have mainly conducted our research for the three most common types of disease as well as one disease-free eye image. Collected images are in different sizes which we resize to a fixed size. Our dataset contains a large amount of data to ensure the performance of the system. Firstly, we split our dataset into two parts, namely train and test datasets. The training dataset contains 80% of the whole dataset whereas the test dataset contains 20% of the data. We have employed six pre-trained CNN model on our training dataset.

In classical CNN method include several steps to obtain best solution for one analysis. It clearly visible in figure 2, convolutional neural network (CNN) scheme for healthy or sick decision. In this study methodology can be explained in easy way. Input image dataset need some pre-processing applications after that image data trained for the neural network. Then decision function classified image healthy or sick. Newly produced trained image data compared with pre-trained

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image data. That's why classification function select best solution in every analysis.

Then what are we going to do that last layer that every particular model has to remove? Because the pre-trained model has thousands of layers. Though we worked on four categories of images. So, we added the 4 output layers. This is called the art of algorithm of transfer learning. In all the models, 10–3 has been used as the learning rate for both the Adam and RMSprop optimizer. To reduce the error rate, we used Adam and RMSprop optimizer equations, (1) and (2), which update network weights iteratively in the training dataset by replacing the stochastic gradient descent method. Adam and RMSprop optimizer play a key role to minimize the error. To perform our work, all the deep learning models have been trained with GPU support. Then we needed to collect our required images and pre-process them. After that, we applied different deep learning algorithms and analysed their result.

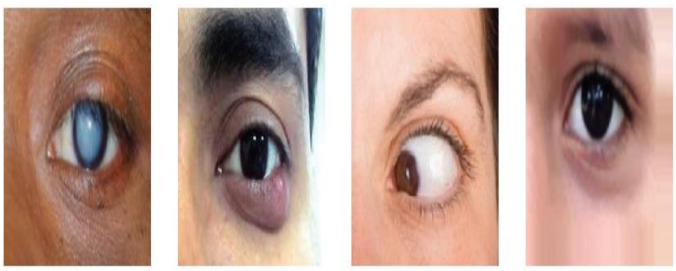
Description of disease

There exist many eye diseases among which some are very much prevalent in India, especially in rural areas, like cataract, chalazion, squint, and glaucoma. Figure 1 shows a representative image of each of these diseases. These diseases are discussed here

• **Cataract:** People are affected by this disease when the eye lens becomes cloudy. Even though it starts with minor problems; gradually it becomes the worst problem. During the early stage, prescription glasses can help us but later surgery is mandatory in this regard.

• **Chalazion:** A chalazion slow-growing small lump or cyst within the upper or lower eyelid but is more common in the upper eyelid. These are not very painful and last for higher than a few weeks, but they can affect the eye to become more watery and mildly irritated.

• **Squint:** The Squint is a condition in which one eye is turned in a direction that is different from the other eye. Normally, six muscles work together for eye movement but patients with this disease have problems with eye movement.



(a) Cataract (b) Chalazion (c) Squint (d) Normal

Fig.1 Three common eye diseases in Bangladesh. (a) Cataract eye. (b)

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Chalazion eye. (c) Squint eye and, (d) Normal eye (disease-free

SYSTEM ARCHITECTURE

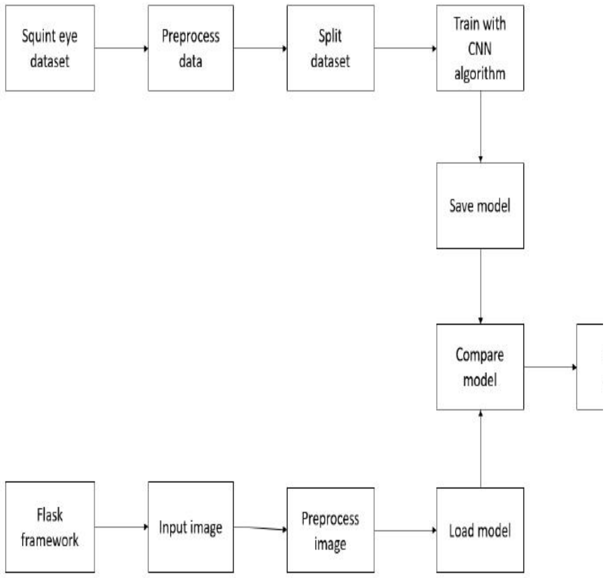

Fig.2 System architecture

IV. IMPLEMENTATION

Code is produced from the deliverables of the design phase during implementation, and this is the longest phase of the software development life cycle. For a developer, this is the main focus of the life cycle because this is where the code is produced. Implementation may overlap with both the design and testing phases. Many tools exist (CASE tools) to actually automate the production of code using information gathered and produced during the design phase

THE EYE DETECTION PROCESS USING CNN Model

The eye detection processes this section presents the detailed process of the proposed eye detection method. The method consists of six steps as follows:

Step1: The boosted cascade face detector is applied to locate the face region. However, 100% eye detection accuracy could not be obtained using the face detector. Hence, the wrong face detection images are manually corrected.

Step2: The detected face is normalized to an image of size 200 ×200 pixels.

Step3: In general, eyes always exist in the top half of the face. Hence, the eye search region is limited to the top half of detected face region. With the human face geometric structure, the search region is rebuilt as: Wsr ≈12WF×γW, Hsr ≈12WF×γH(15)where WF is the width and height of face image (width =height), Wsr and Hsr are the width and height of the search region, γ Wand γ Hare the adjustment coefficient factors of width and height of search region respectively. The search region of size Wsr ×Hsr pixels on the human face.

Step4: The search region variance image is calculated. Then, many overlapped windows of size 16 ×8 sub-blocks of size 3 ×3 pixels with 3pixel interval (1 sub-block of size 3 ×3pixels) are built to detect the

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candidate eye regions on the variance image search region.

Step5: With the Eq. (4) the correlation values between the extracted vector block and EVF are calculated. Among them the correlation values with higher 0.32 are counted into the set of candidate eye regions. Through, some examples of candidate eye regions are obtained.

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Step6: From most of non-eye images in the search region can be observed to have been dis-carded by EVF. The trained CNN extractor are then employed to select only two regions which are the most possible regions of left and right eyes from the candidate eye images

V. RESULTS

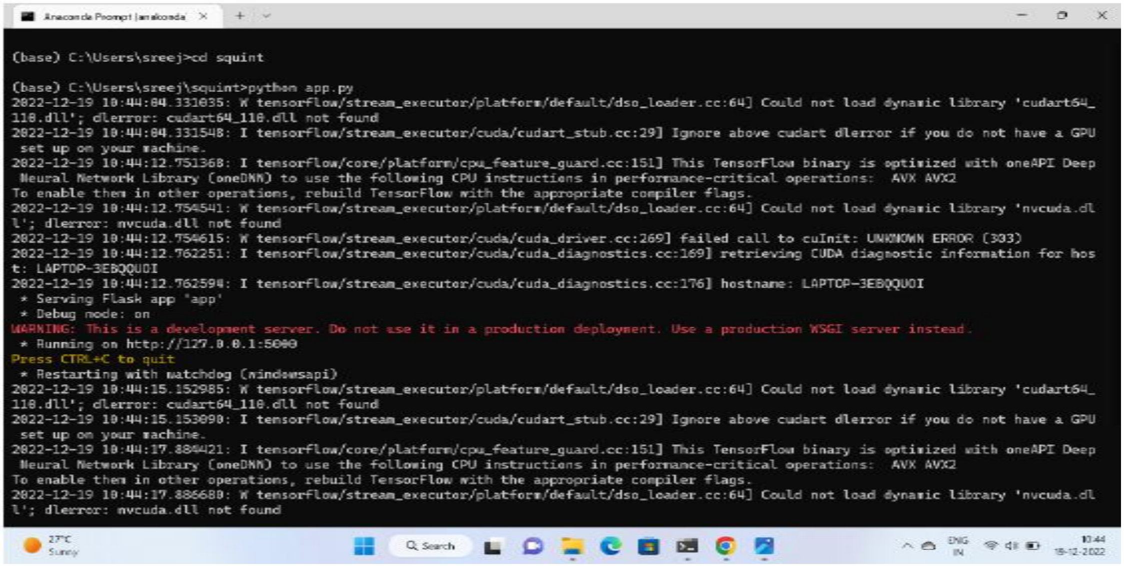

Fig.3 Command prompt to open website

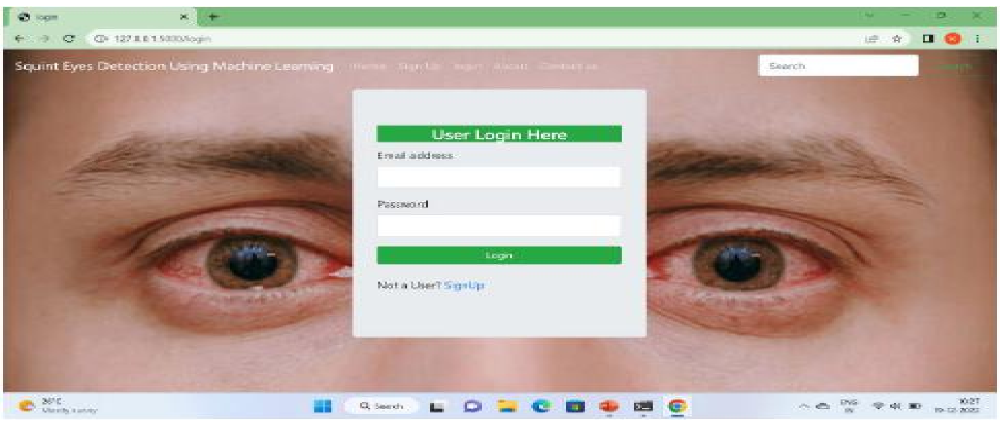

Fig.4 Login page

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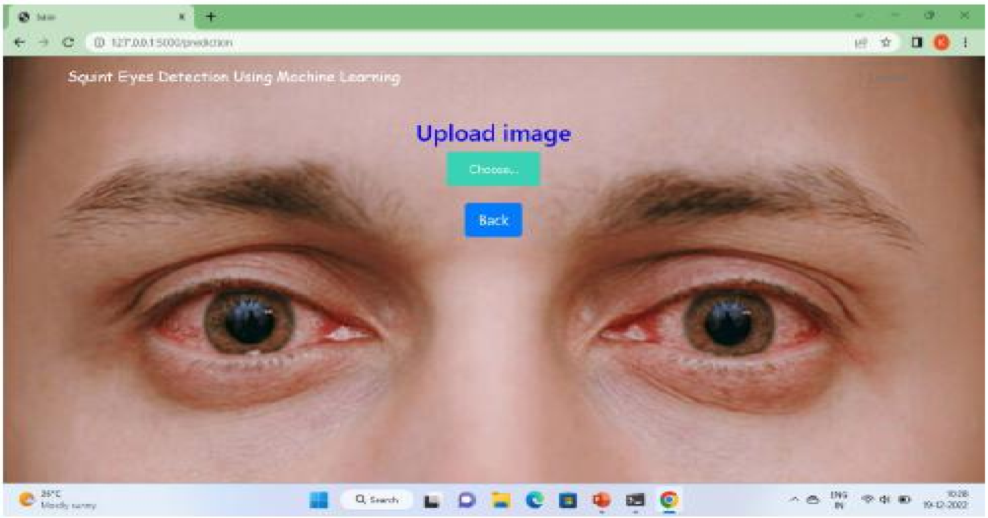

Fig.5 Image of uploading

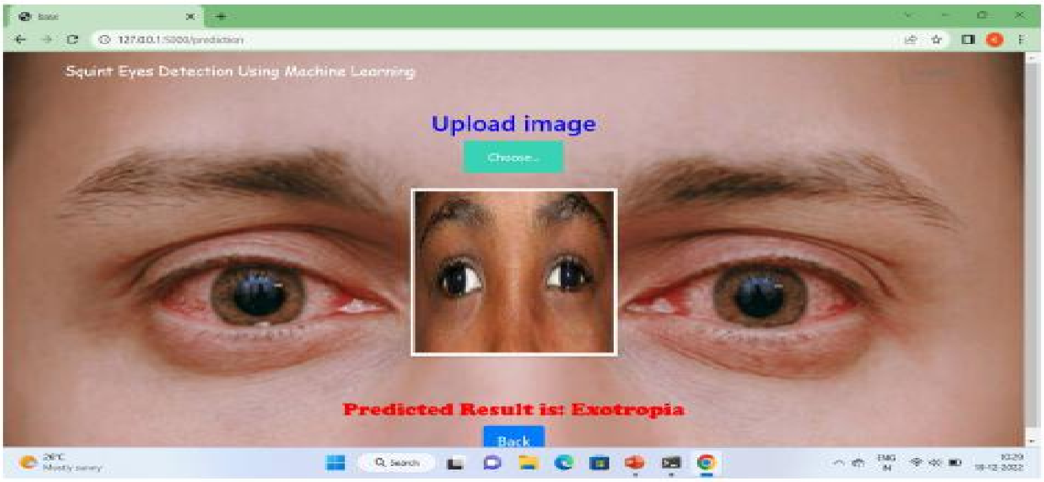

Fig.6 Result of squint eye type-1

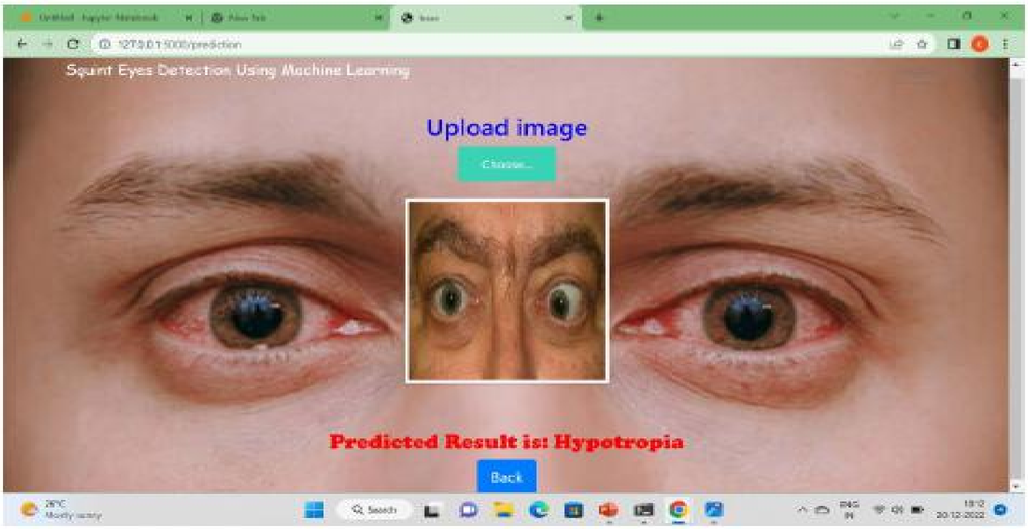

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Fig.7 Result of squint type-2

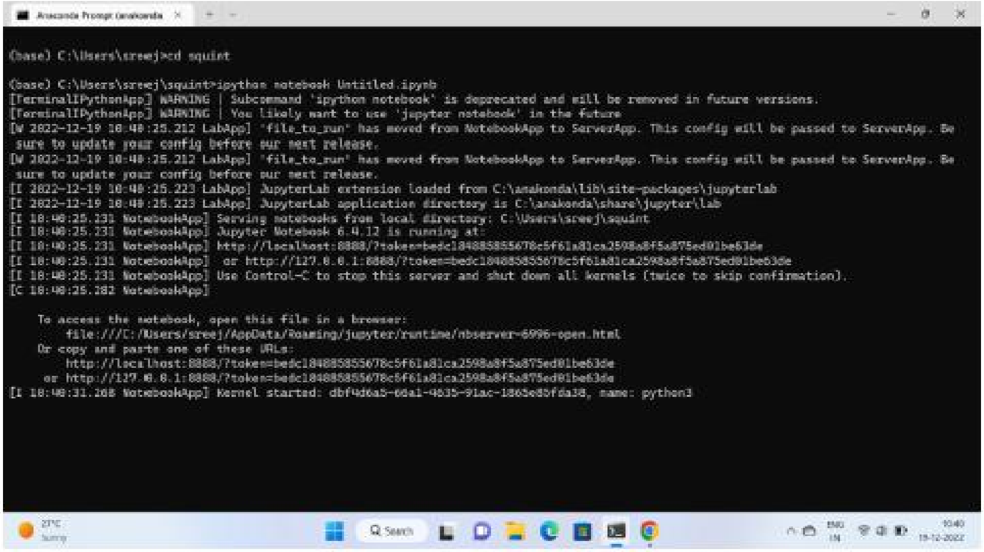

Fig.8 Command prompt to open jupyter site

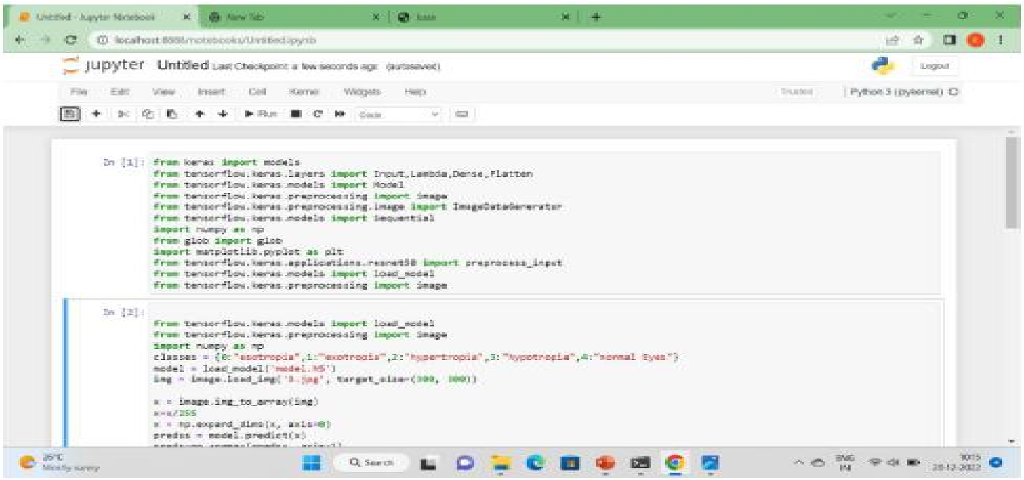

Fig.9 Input image

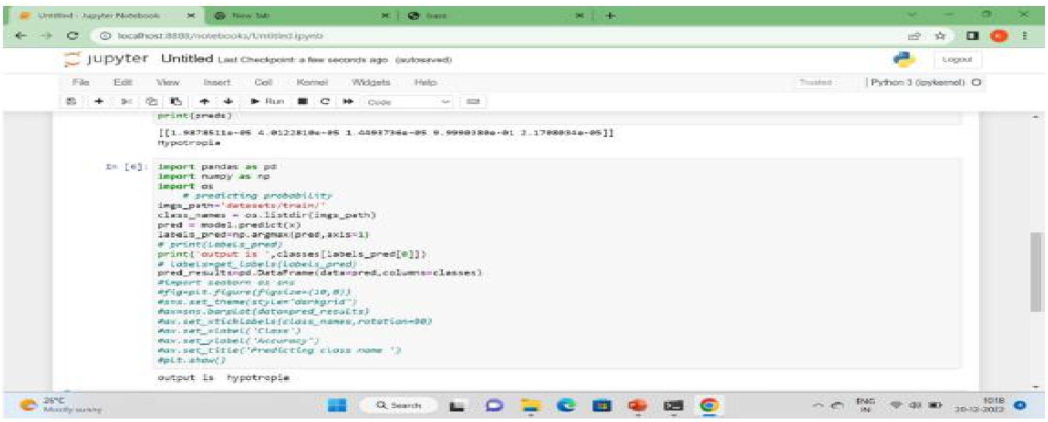

Fig.10 Result of squint eye type-1

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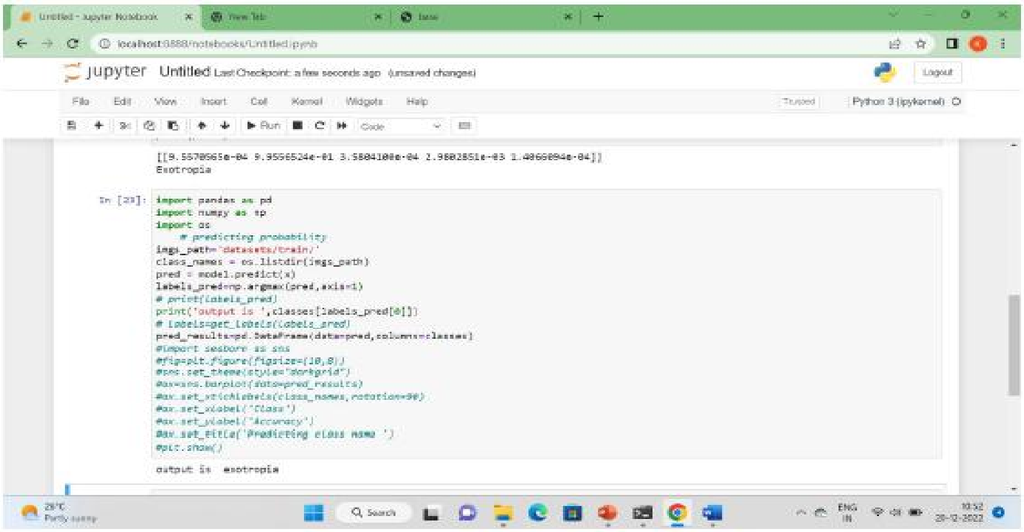

Fig.11Result of squint eye type-2

VI. CONCLUSION

In this study, in order to provide squint screening for patients who cannot visit hospitals in remote areas, we propose an automatic strabismus screening method that compares CLR on both eyes in a facial image. The method employed a face detection model, facial landmark detector, automatic binarization, and the least square method to locate the coordinates of the iris edges and the reflective point centre.

These estimated coordinates are used to compute CLR ratio for determining whether a patient is suffering squint. The experimental results with several images demonstrate the effectiveness of the proposed method. The CNN has the advantage of extracting various latent eye features, and acts as this system's automatic feature extractor.

From the reported accuracy of the system, we believe that this eye detection method can provide enabling technology to applications in the future. All experimental results have demonstrated the effectiveness of our method. More importantly, the proposed system is objective, non-invasive, and automatic. It could be a potential powerful alternative for squint diagnosis.

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