

# A survey on Deep Learning Based Eye Gaze Estimation Methods

**S. K. B. Sangeetha**

Assistant Professor (Sr. G), Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, India

**E-mail:** sangeets8@srmist.edu.in

## Abstract

In recent years, deep-learning systems have made great progress, particularly in the disciplines of computer vision and pattern recognition. Deep-learning technology can be used to enable inference models to do real-time object detection and recognition. Using deep-learning-based designs, eye tracking systems could determine the position of eyes or pupils, regardless of whether visible-light or near-infrared image sensors were utilized. For growing electronic vehicle systems, such as driver monitoring systems and new touch screens, accurate and successful eye gaze estimates are critical. In demanding, unregulated, low-power situations, such systems must operate efficiently and at a reasonable cost. A thorough examination of the different deep learning approaches is required to take into consideration all of the limitations and opportunities of eye gaze tracking. The goal of this research is to learn more about the history of eye gaze tracking, as well as how deep learning contributed to computer vision-based tracking. Finally, this research presents a generalized system model for deep learning-driven eye gaze direction diagnostics, as well as a comparison of several approaches.

**Keywords:** Computer vision, Deep learning systems, Eye gaze tracking and infrared image sensors

## 1. Introduction

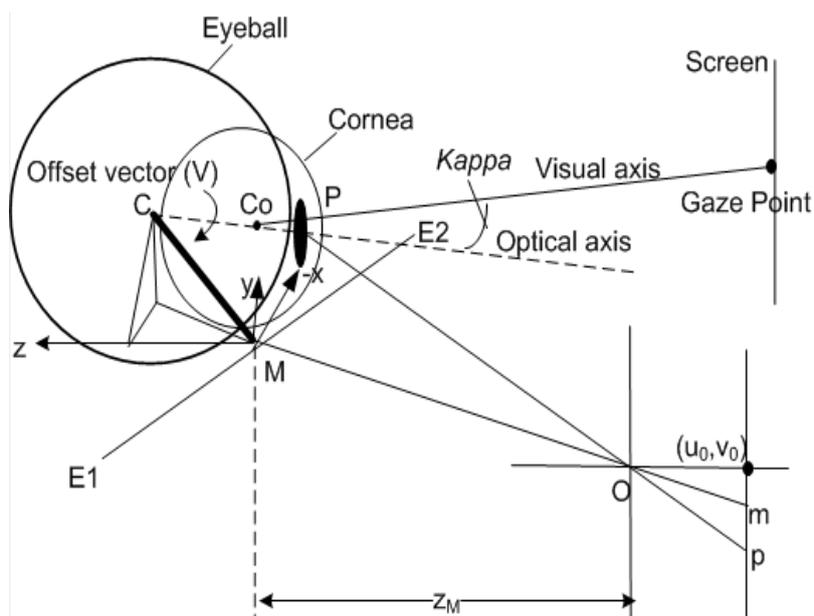
Human emotions and cognitive circumstances are crucial in designing a natural Human Computer Interaction (HCI) framework. Through technologies that can recognize human

affective and cognitive processes, the relationship will become more normal. Mental intelligence can aid computer systems in communicating effectively with humans. Many studies on the use of facial expression in human-computer interaction have lately been published. The mechanisms and emotions of human cognition are shown in great detail by human eyes. Eye movement patterns reveal information about weariness, illness, and other factors. Pupil dilation has also been employed as an indication in the study of cognitive processes. The nature of eye movements is well-known. Several studies have gradually been applied to the utilization of eye movement patterns as biometrics. The majority of facial work is done on a computer. However, the current development of wearable technologies such as Google Glass and other Virtual Reality Gauges gives consumers more opportunities to apply eye tracking techniques to examine their affective and cognitive processes [1].

Eye access points are the patterns in which people's eyes travel as they enter their memories. Mental details can be found in the patterns perceived in this non-visual direction of the gaze. Eye access to knowledge from the direction of eye gaze delivers information about mental processes, according to the concept of neuro-linguistic processing [2]. These motions are said to be linked to neurological networks that deal with memory and sensory information. Many cognitive processes can be learned through the travel of the iris in the socket. Each way of looking non-visually is linked to different cognitive processes. Although the EAC explanation isn't perfect, new investigations have discovered a link that warrants more investigation. Information recovery systems can perform better if the context is known. In HCI, context can be important for understanding cognitive states [3].

By providing a simple and practical input mechanism or delivering important information on user attentiveness, eye tracking can improve the quality of life of motorized users. Previously, eye object tracking was limited to psychiatric research facility conditions or disabled persons, frequently requiring government funding and expensive hardware. Glance direction of an eye alone can easily be calculated. The complexity of this undertaking grows

when there are fewer pixels, motion blur, less perfect changing illumination, and ambiguity when describing the magnitude of the eyeball or the shape of the iris [4].



**Figure 1.** Eye Gaze Estimation Process

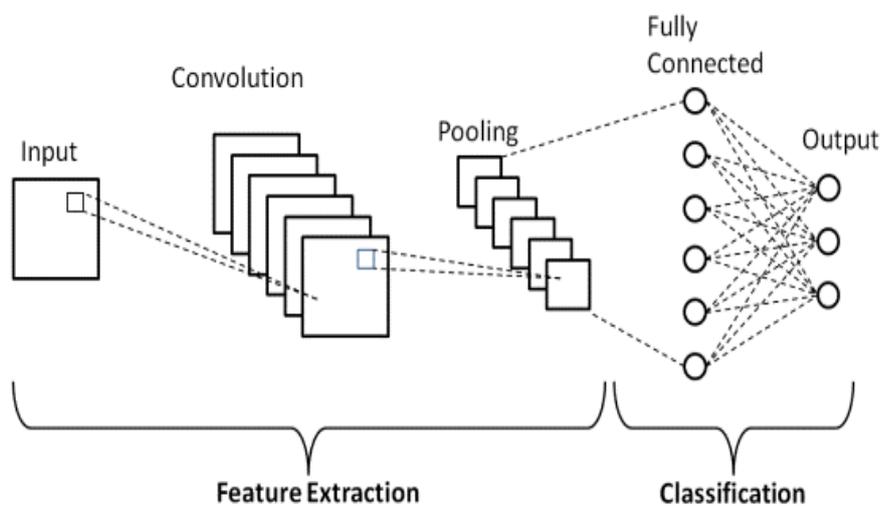
To better categorized

- (a) Poor sensor quality or unidentified environments and
- (b) Wide variations in the appearance of the eye area.

(c) Anatomical variations between people, head-positive differences or contextual changes in decorations such as eye lenses or cosmetics may be further differentiated [5].

Neural network-based techniques are employed for head-position tolerant viewing. The eye pictures cropped in the user's eye and the related coordinates at a particular moment on the screen make up the training data. Networks and a skin color model are utilized to detect facial and ocular areas. With low-eye photos, an artificial neural network improved Particle Swarm Optimization can be employed for rapid, precise, and robust view estimates [6].

Neural networks can be utilized for a variety of entries, but they're most typically employed for 2D input with color channels because of their image quality. 1D CNNs, which are commonly used in time series, and 3D CNNs, which control spatial frames or time frames in 3D space, both for gravimetric and time series data, are two more types of CNNs. To approximate a linear equation of gaze co-ordinates and pupil-glint vectors, use an artificial neural network. Simple regression approaches are less accurate than this methodology [7].



**Figure 2.** CNN Process

The goal of this paper is to inform readers about existing deep learning for eye gaze tracking and to assist researchers in implementing deep learning-driven image processing. This work's key contribution is

1. It started with a foundation of eye gaze tracking.
2. Outlined the need for deep learning in eye gaze tracking and the issues that it poses.
3. Described the system model for deep learning researchers who want to use deep learning to track eye gaze.
4. A comparison of different eye gaze tracking methods.

In the foregoing points, this survey differs significantly from previous recent surveys. It provides the same amount of information as before. The following is a breakdown of the paper's structure. The second section covers the basics of eye gaze tracking. The deep learning system model for eye gaze tracking is discussed in Section II. The comparison of several algorithms is briefly described in Section IV, followed by a conclusion in Section V.

## 2. Related Study

### A. Outline of Eye Dynamics

Clinicians have identified or screened a range of ailments, including balance problems, diabetic retinopathy, strabismus, cerebral sclerosis, and others, for the therapy of eye dynamics, such as 3D spatial (horizontal, vertical, and torsional) dilation and extraction. Eye motion is investigated in the human ophthalmology, vestibular, and neuro-otology systems. The fundamental component of a diagnostic or screening system is a dependable eye motion monitoring system. We all know that aberrant eye movement can indicate neurological, optical, and other health problems. The vestibular system is the most commonly investigated topic in both research and clinical trials (equilibrium). An irregular movement in the eye could be a sign of disorders like Parkinson's disease, diabetes retinopathy, and so on [8].

Equilibrium is the result of the interaction of three systems: the vestibular system, vision, and the central nervous system. The vestibular organ is responsible for two functions. First, an object's movement and spatial orientation are affected by gravity. There are utricle perpendicular channels in the inner ear. Hair cells in each channel can detect fluid shifts and provide data about acceleration and head tilt to the central nervous system. Second, while the head and body are moving, the vestibular system monitors eye movements in a way that allows the eye to acquire healthy and focused images. The presence, absence, and degree of eyerosis generated by various body movement stimuli can be utilized to indirectly assess vestibular function. The eye motion examination and follow-up will provide important information in the identification of vestibular system issues.

The positioning eye has six degrees of freedom, consisting of three socket changes and three twists. Transitions are typically brief and unnoticed. The eye rotates in three directions: horizontally, vertically, and torsionally. Torsional motions are defined as the rotation of the eye around its axis along the line of vision. The eye is never entirely relaxed, even when it is focused on a goal. Fixed eye movement is the "fluctuation" of the eye when attempting to keep the retina steady over a stationary object; it is unintentional and linked to brain stem activity. The eye produces a quick squatting motion when it seeks to focus on a new object. In most circumstances, the eye reaches the new place quickly and without much oscillation or correction. Overshooting is infrequent and to some extent expected. There is a 200 millisecond delay between the target hop and the next hop. As well as the saccade that was elicited [9, 35].

Irregular saccades, which can be detected by attributes such as velocity, precision, and ocular delay, may be used to identify neurological infections. Nystagmus is an involuntary rhythmic eye movement that occurs when the eye travels swiftly one way (fast phase) and gradually the other direction (slow phase) (slow phase). Nystagmus can be horizontal, vertical, or torsional. The visual pattern can be used to diagnose most nystagmus-related eye disorders. There is a 200 millisecond delay between the target hop and the next hop and the saccade that was triggered. Irregular saccades, which can be detected by attributes such as velocity, precision, and ocular delay, may be used to identify neurological infections. Nystagmus is an involuntary rhythmic eye movement that occurs when the eye travels swiftly one way (fast phase) and gradually the other direction (slow phase) (slow phase). Nystagmus can be horizontal, vertical, or torsional. The visual pattern can be used to diagnose most nystagmus-related eye disorders. Electro- and computing devices are commonly used in eye movement monitoring systems. They can track your eye movements in a quantitative, accurate, and repeatable manner. It aids in the detection of tiny alterations such as high intensity, low amplitude, and accurate disease identification or chronic illness reduction [10].

## B. Impact of Deep Learning In Eye Gaze Direction

Eye gaze signals are important in human communication and engagement. An outsider can tell how you look and thus what you see by the direction of your eyes. This could be a general-interest object or the observer himself. As a result, the direction of your gaze serves as a clear social signal for your intentions and future actions, and it is crucial in many social behaviours that rely on interpersonal communication, such as learning and cooperative activities. Understanding the methods by which other gazes are perceived and understood became an important focus of interest in the emerging subject of social neuroscience.

Because it is at the intersection of visual awareness and social awareness, the visual experience is an essential concept to examine. As data is captured from the stream of sensible signals transmitted from the retina in the cortex, neuroscience and brain imaging studies have begun to reveal the function of subcortical structures such as the vestibular nuclei, amygdala, and pulvinar, as well as the relationship of these systems with the higher level of attention. Because it can be specified over the continuous dimension (e.g., with horizontal eye fluctuations of roughly 40° left to 40° right) and has a brain base recognized within the temporal lobe sulcus, gaze direction is a relatively traceable feature of our social experience for research. This can be used as a model framework for social neuroscience in order to get a feel of the vision's direction [11, 36].

A gaze classification CNN calibration-free real-time system is used as an example. The look is then divided into seven directions for the left and right eyes by two CNNs. Foveated rendering and gaze-contingent focus are provided by increased and virtual reality applications based on CNN gazes tracker. The profound learning model is adjusted to account for changes in eye color and skin tone, as well as enlightenment and occlusion. For gaze-direction prediction, multi-scalar convolutions and a mixture of eye pictures are used to derive deep properties. Deep learning approaches were effectively applied in tough settings such as those with changeable lighting, uncontrolled surrounds, and unrestricted head mobility [12].

### C. Computer Vision in Relation with Eye Gaze Estimation

One or more digital cameras, infrared infrastructure LEDs, and a user-facing display device are the core components of video-based surveillance systems. The user calibration, video seizure of the user's visual and ocular areas, eye recognition, and visualization with visual coordination at the screen are all key assumptions in the passive video surveillance process. Video eye monitoring systems, whether invasive or non-invasive, can help. The bright light or infrared light is separated into two more groups in each category. One or more cameras are generally used in invasive systems. Human Computer Interactions' most fascinating issue is non-invasive or remote systems (HCI). The number of different gaze tracking methods utilized to track the point of view is astounding. A single-camera eye tracker and a multi-camera eye tracker are both group-able remote eye tracking devices [13] [14].

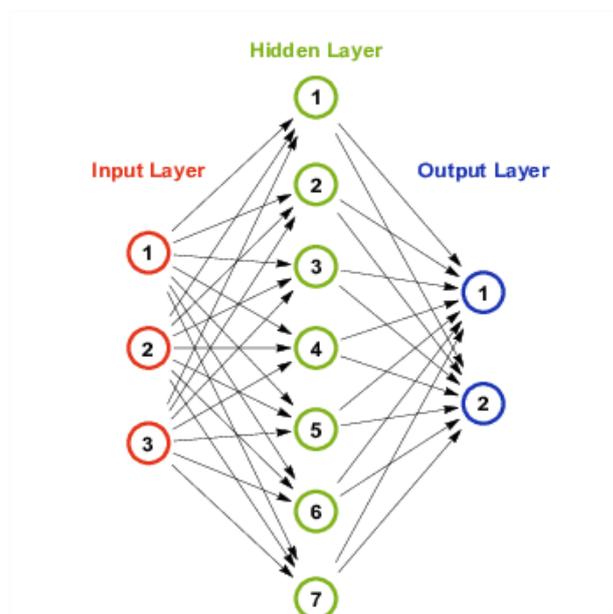
Infrared light is used to illuminate the eye in most video eye trackers. Corneal reflection occurs when light reflects off the cornea of the eye. Glint has been employed as a visual reference for gaze assessment in the majority of recent studies. When the eye or head moves, the distinction pupil-glint vector remains constant. The splint changes when the head moves, but the location of the splint changes less visibly as the direction of view changes. The above-mentioned fixed camera systems' main flaw is their small field of view, which makes it difficult to acquire high-resolution photos. The results are better when a variety of light sources are used instead of a single source. The first single-camera remote eye tracking device was a professional system with great accuracy and a wide range of movement tolerance [31].

A vast field of view is produced to allow for unfettered head movement, but high resolution photographs are required to adequately measure the gaze. It's crucial to have a small viewing field. To achieve these goals, several cameras use wide-angle or moving narrow-angle cameras. For multiple literature camera systems, either employ a distinct camera for each eye or employ a head position tracking camera to compensate for changes in head position. To determine the gaze, add all of the camera's details together. The pupil-glint vector can thus be calculated from the collected ocular pictures. Both cameras are also modified to provide a

stereo viewing system that allows for the determination of a 3D pupil center coordinate. The gauze mapping feature is entered when the decided center for 3D students is coupled to the retrieved 2D pupil-glint vector [15].

### 3. System Model

CNNs are a type of deep neural network used in deep learning to primarily evaluate visual pictures. The organization of the cortex in the brain has inspired them. The visual cortex is the largest part of the brain that receives and processes visual information from the eyes. CNNs are comparable to ordinary neural networks in that they have many neurons, a large number of them, and learning disruption. Each neuron in the network approves the input, performs dot product operations, and automates non-linear dot operations. CNN architectures, in particular, assume that all inputs are images so that users can encode such properties in the architecture [33]. Multiple convolution layers and bundles, non-linearities, and finally entirely connected layers and output layers make up a CNN. In the first three layers, functions are retrieved, and the complete connected layer can be identified.



**Figure 3.** Convolutional neural network framework for eye gaze tracking

The eye-tracking procedure consists of three key steps: locating the presence of the eyes, understanding the precise locations of the eyes, and controlling recognised eyes frame by frame. The pupil or iris centre is used to detect the eye's location in general. The gaze computation is a method for determining and tracking a person's 3D vision or simply when they look. A gaze tracker is a system or technology that allows you to track your gaze by studying the movements of your eyes. A glide tracker does two tasks at once: locating the eye in video or images and monitoring its movements in order to determine the glide path. Finding the eyes is the initial step in eye detection. Eye detection is based on image or video data that has been modelled with eyes. A model eye should be realistic enough to account for the eye's density and appearance variations while still being constrained enough to be computationally efficient.

Outward factors such as the degree of openness of the eye, size variations, head position and reflectivity, and pupil obstruction make eye identification and monitoring challenging. The subject's race, light conditions, texture, iris placement, and eye status within the eyebrow all have an impact on the eye's appearance (open or closed).

The visual axis, for example, or the optical axis, are the focal points of the view. The line that connects the centre of the cornea to the fovea is the visual axis that creates the visual line. The lens, also known as the gaze line, is a line that runs across the pupil's centre, cornea, and eye world. The corneal core is the eye's nodal point. At the nodal point of the eye, an angular offset spans the visual and optical axes. Knowing how the corneal or ocular core is can be used to precisely calculate the head location in 3D space. Gaze tracking device components are set up in order to establish a sequence of relevant variables in the calibration process, as explained below.

- Geometric set-up calibration is required to identify relative dispositions and positions of the various instruments (e.g., light sources and cameras).

- For corneal curvature prediction, individual measurements are taken between the physical and visible poles.
- The system used to validate the mapping eye-gazes.
- The sensor is calibrated to take into account the camera's inherent properties.

Some data, such as human dimensions, are measured only once, whereas other characteristics are determined for each session by staring at a particular number of points on a display. Device-related factors such as physical and geometrical angle parameters, as well as position between multiple devices, are pre-calibrated before usage. A device is said to be completely calibrated if the geometrical configuration and camera characteristics are correctly known [34].

#### **4. Discussion and Analysis**

For image-based eye detection, several techniques have been proposed. Traditional and profound eye detectors for eye detectors can be divided into two groups. The geometrical properties of the eye are frequently matched by traditional eye detectors. The sensors can be classified into two categories. The geometric model is the first subset. The curvace of isophotes was utilised to create a voting mechanism for the position of eyes and pupils [16]. [17] Suggests a method for finding eye pupils based on a random regression set of trees. [18] Suggested using picture gradients and squared dot products to detect pupils. The template is the second subclass. RANSAC was utilised to create an elliptic equation in the midst of the students. The Inner Product Detector for eye position is demonstrated using correlation filters. Traditional eye sensors can frequently yield decent results, but they can readily fail when outside light or facial occlusion changes [19].

Deep eye sensors are likewise divided into two types. Conventional extraction and cascading grouping are the first two subclasses. [20] Used the Haar Wavelet Support Vector Machine (SVM) for quick categorization. An Oriented Gradients (HOG) Learning Histogram

for an effective eye sensor is proposed [21] in conjunction with SVM classification algorithms. [22] Integrated form analysis with facts on the apparent eye center's self-similarity. To detect eye areas, a limit based on geometric features and neural classification was developed. [23] Has proposed a framework for cascade regression to estimate both the position of the eyes and the state of the eyes at the same time. [24] proposed that eye candidate regions be generated, and that multiple iris shapes be employed to quantify them using the HOG and cell's mean strength features. With the rise of profound learning techniques, several researchers have used the NRC to train second-class eye detectors.

**Table 1.** Comparison analysis of deep learning approaches

Method	Approach	Errors	Metric
Computer Vision + Convolutional Neural Network [29]	Visible-light mode /Non-Wearable	Nil	Mean errors < 7.75°
Convolutional Neural Network [32]	Visible-light mode /Non-Wearable	Nil	Accuracy - 92.4%/ 9 gaze zones
Convolutional Neural Network [20]	Visible-light mode /Non-Wearable	Nil	Mean errors < 3.64°
Deep Convolutional Neural Network [15]	Visible-light mode /Non-Wearable	Nil	Mean errors < 5°
Standard Neural Network [19]	Visible-light mode /Non-Wearable	Nil	Mean errors =10.8° for cross-dataset Mean errors < 5.5 ° /cross-person
Deep Convolutional Neural Network [16]	Visible-light mode /Non-Wearable	Nil	Mean errors < 2° at training < 5° at testing
Convolutional Neural Network [4]	Infrared mode /Non-Wearable	< 6 pixels	Gaze-estimation bias = 0.72°

[25] Describes a CNN-based Center detection algorithm. Two related convolutional neural networks were employed in research by [26] for ground to fine pupil position detection, and the authors recommended downscaling the image to save device costs. [27] Used 68 characteristic points describing the eye contour at 12 places to train the facial landmark sensors to define the model. Deep learning algorithms were more resilient and trustworthy, in contrast to traditional methods. However, efficiency is still an issue. The portraits of people's faces are usually larger. A considerable number of computer resources are used if the CNNs conduct an overall picture search. Only selected candidate regions must provide CNNs quickly and efficiently in order for candidate regions to be proposed. In some applications, such as eye monitoring systems and eye detection, the left/right eye classification and eye centre positioning, as well as the determination of eye regions, are critical. However, most existing detectors are ineffective at determining the regions of the eye, distinguishing between the right and left eyes, or detecting the eye's centre [28, 30].

## 5. Conclusion

In terms of measuring and evaluating cognitive level, inspiring an interface design, discovering a behavioural response based on user data, improving teaching quality by improving the teaching framework, promoting the use of technology, and improving educational standards, eye tracking technology has proven its efficiency and effectiveness. Tracking eyes and views is a hot topic in advanced assistive technology research. It's especially critical that safety researchers take this seriously because one of the leading causes of traffic accidents is visual distraction. Deep learning algorithms were effectively used in tough settings such as those with changeable lighting, endless backgrounds, and free head movements. The fine-tuning of pre-trained CNN models is common practise, and it has improved overall performance. The dense layers can be taught in reduced predicted error with almost minimal time by fine-tuning the pre-trained CNN models. However, some areas, such as establishing an adaptive framework based on the need for user's cognitive load levels as assessed by eye

tracking data, have received less attention. By boosting information transfer and retention while maximising the trainee's time, a framework like this would improve training. Furthermore, present eye monitoring systems and research methods suffer from cost and software integration issues, preventing the development of commercially viable goods or tools for broad use.

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### Author's biography



**S. K. B. Sangeetha** is currently working as an Assistant Professor (Sr. G) in SRM Institute of Science and Technology, Chennai, India. She has completed her PhD from Anna University, Chennai. She completed her Master's Degree from Dr. Mahalingam College of Engineering and Technology, Coimbatore and the Bachelor's Degree from Christian College of Engineering and Technology, Dindigul, both graduated from Anna University. She has 14 years of Teaching and Research experience which has helped her to gain immense knowledge in myriad fields of Computer Science and Engineering. She is a life member of Indian Society for Technical Education and The Indian Institute of Engineers. She has written five books for the engineering curriculum. She has published around 66 research papers in several international and national forums which include various ISI, Scopus, IEEE indexed international conferences as well. She is also an editor and reviewer for some international journals as well.