**ARTIFICIAL INTELLIGENCE AND ITS EFFECTIVE ROLE IN OPTOMETRY**

Artificial intelligence is a term to accomplish a task by a computer, with the least involvement of human beings. It was widely accepted after the invention of robots. So Artificial Intelligence and machine learning are the most trending and computer-based technologies can be correlated but never be used as synonyms. This revolutionary concept is frequently used in various fields, but in ophthalmology, it has a concern with the diagnostic tool. Diabetic retinopathy, age-related macular degeneration, glaucoma, retinopathy of prematurity, age-related or congenital cataract and retinal vein occlusion are examples of such diagnostic solutions.**[1, 2]**

**INTRODUCTION:**

Artificial intelligence (AI) is a field having a combination of computer science with strong and enriched datasets, to solve the related problem. It is the science and engineering of making intelligent machines, based on computer programs, but AI does not have biological observation to confine itself. (John McCarthy) Stuart Russell and Peter Norvig published the first leading textbook on AI, “Artificial Intelligence: A modern approach.**[3]** Several concepts of artificial intelligence (AI) have been introduced in the easiest words-

*Artificial intelligence is a technology by which we can create intelligent systems to simulate human intelligence.* **[1]**

Artificial intelligence uses algorithms (machine learning) which work with their intelligence (deep learning neural networks). AI has different capabilities so classified into three types **[1]**

1. Weak AI
2. General AI
3. Strong AI

Therefore machine learning extracts knowledge from past pooled data to make decisions instead of any pre-programmed data.

The capability of making accurate predictions or decisions of machine learning based on massive amounts of structured and semi-structured historical data. It works only for specific domains and is used in various places like Google search, Email spam filters, Facebook auto friend tagging, etc. It is further divided into- **[1]**

1. Supervised learning
2. Reinforcement learning
3. Unsupervised learning

**TYPES OF ARTIFICIAL INTELLIGENCE:**

1. Weak AI known as narrow AI or Artificial Narrow Intelligence (ANI) is trained and focused to perform specific tasks. Weak AI drives most of the strong applications throughout the world such as Siri (Apple), Alexa (Amazon), Watson (IBM), etc.
2. Strong AI is divided into Artificial General Intelligence (AGI) which is a theoretical form and its intelligence is equal to the human, so it can solve the problem, learn and it can schedule for the future. The second one is Artificial Super Intelligence (ASI) also known as super intelligence which surpasses the intelligence and ability of the human brain.

**BASICS OF AI: [4]**

The term artificial intelligence was invented in the 1950s. Dr Abramoff and others try to compare the human brain’s mechanisms with “neural networks” and researchers started working on advanced analysis of automated imaging.

Nowadays AI systems automatically detect and measure pathologic conditions through imaging of the eye. Simple automated detectors are a simple form of AI, which gives a mathematical description (rules-based algorithm) to detect the patterns of incoming images (pattern recognition). Posi­tive hits produce a diagnostic indicator.

1. At the earliest (**basic machine learning**), it was not easy to design computer algorithms to obtain a final result therefore it was turned towards machine learning, where features of diseases were introduced to the algorithm and instructed to correlate it with the neighbour network, at their output result.
2. **Advanced machine learning** has two interconnected layers of computing units called neurons which could resemble the human brain. Among the first layer, inputs of the disease are introduced and forwarded to the next layer through a neural network to achieve diagnostic output. Thus neural network learns it through the associated specific outputs.
3. **Deep learning with convolutional neural networks** (CNNs). the deep learning term has a concern with multiple interconnected layers of neurons through the pixel or voxel intensities and is used to finalize their result through repetition and self-correction i.e. thinking. So CNN algorithm teaches itself through the pixel or voxel intensities. In any adverse result output, the algorithm adjusts its parameters (weights) to lower the error (synaptic strength) till the being agreed of the network is to the optimized result.
4. **In disease feature based versus image-based (black box) learning**, the clinical characteristic of the disease are designed by the ophthalmic researcher for machine-learning algorithms and if necessary then it can be adjusted. However, Google Brain (2016) reported an unsupervised black box system; the algorithm takes decisions correctly in itself for the identification of diabetic lesions through photo­graphs but could not say what the lesions look like. One of the vitreoretinal subspecialist consultants of the Google Brain project said it is exciting with deep learning, it is not yet sure what the system is looking at, but it arrives at a correct diagnosis like an ophthalmologist.

**PRINCIPLE OF ARTIFICIAL INTELLIGENCE:[2]**

The AI devices have two specific areas, machine learning and natural language processing.**[5]** Machine learning provides algorithms to create automatically a complex correlation between the available input data (training set) and performance standard (validation set)[**[6]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b7) to create a successful decision over the test. Performance standards need a large number of data from authoritative experts.

The deep learning models are powerful tools for the identification and classification of images and have two subtypes-

1. Convolutional neural network (CNN)
2. Massive-training artificial neural network (MTANN)[**[7]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b11)

Both networks have many layers, but the convolutional neural network works within the network and the massive-training artificial neural network, works outside the network, but at the last of the process convolution layer is connected to the whole, as CNN needs many details for the finalization of the result.**[8]**

**HISTORY OF ARTIFICIAL INTELLIGENCE:** **[3]**

It was a very old thought that the machine can think, but as electronic computing methods grew up with time so many evolutionary milestones have been established-

Alan Turing (1950) published a study, Computing Machinery and Intelligence, answering 'Can machines think?' through the Turing Test to determine the intelligence of machines is the same as that of humans.

John McCarthy (1956) introduced the term 'artificial intelligence' at an AI conference at Dartmouth College and later in the years, Allen Newell, J.C. Shaw, and Herbert Simon create the first time running software program for AI.

Frank Rosenblatt (1967) introduced the “Mark 1 Perceptron” the first computing software based on a neural network and onward a year later, Marvin Minsky and Seymour Papert publish the book “Perceptrons” holding the landmark work on neural networks.

Neural network (1980) which used a backpropagation algorithm is used widely in AI applications.

IBM’s (1997) Deep Blue was won by the world chess champion, Garry Kasparov and later on again in 2011 IBM’s Watson was won by champions Ken Jennings and Brad Rutter at Jeopardy.

Baidu's Minwa (2015) uses a convolutional neural network in a supercomputer, to identify and categorize images with a higher rate of accuracy than the average human.

Deep Mind's AlphaGo program (2016), based on a deep neural network, beats the world champion Lee Sodol, the Go player, in a five-game match and thereafter, Google purchased this software.

A rise in large language models (2023), such as ChatGPT, creates an enormous change in the performance of new generative AI.

**DIFFERENCE BETWEEN ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING:[1]**

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| --- | --- | --- |
| **Sl No** | **ARTIFICIAL INTELLIGENCE** | **MACHINE LEARNING** |
| 1 | A.I. makes a machine to simulate human management. | M.L. concludes a subset of AI from past data. |
| 2 | The goal of AI is to make a smart computer system like a human. | The goal of ML is to learning of machines through the data. |
| 3 | The main subsets are Machine learning and deep learning. | The main subset is Deep learning. |
| 4 | A. I. has a very wide range of scope. | M.L. has a limited scope. |
| 5 | A. I. performs various complex tasks. | M.L. performs only specific tasks for which they are pre feeded. |
| 6 | A. I. is concerned with maximizing the chances of success. | M.L. is concerned with accuracy and patterns. |
| 7 | The main applications are Siri, customer support using catboats, Online game playing, intelligent humanoid robots, etc. | The main applications are an Online recommender system, Google search, Facebook auto friend tagging, etc. |
| 8 | A. I. is divided into Weak, General, and Strong AI. | M.L. is divided into Supervised, Unsupervised and Reinforcement learning. |
| 9 | It includes learning, reasoning, and self-correction. | It includes learning and self-correction. |
| 10 | A. I. has concern with Structured, semi-structured, and unstructured data. | M.L. deals with Structured and semi-structured data. |

**ARTIFICIAL INTELLIGENCE AND EYE:**

The anterior of the cornea to the posterior of the retina can be achieved by the new automated tool named artificial intelligence helpful as a diagnostic tool. This computerized analytical assessment for medical potential is driven by the efforts of Google and IBM. **[4]**

Regarding ophthalmic applications of AI, the CASNET-based glaucoma consultation program (1976) was introduced clinically by the application of the Machine Learning aspect of Artificial Intelligence.**[**[**9**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R7)**]** Ophthalmic diagnosis becomes easy if data-rich imaging is available through Deep Learning algorithms which are designed on disease-based learning, where the known characteristics of the disease on the image express themselves for the machine to recognize and learn, and the output is verified by the optometrist or clinician. The most running available AI tools are for cornea (keratoconus), cataract, glaucoma and other anterior segment diseases, oculoplastic surgery and retina, concluding diabetic retinopathy (DR), age-related macular degeneration (AMD), and retinopathy of prematurity (ROP).**[**[**10**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R8)**]**

**DIABETIC RETINOPATHY:**

Diabetic Retinopathy is the leading cause of blindness [**[11]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b16) where progressive damage through micro-aneurysm, haemorrhage, exudation, cotton-wool spot and neo-vascularization take place on the retinal vasculature. **[12]**

For diabetic retinopathy most important is fundus examination, the input for micro-aneurysms and haemorrhage comes in a three-layer feed and is forwarded to the neural network for the classification of the different stages of diabetic retinopathy. [Figure1](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/figure/ijo-11-09-1555-g001/)[**[13]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b14). Now the characteristics of the disease are extracted to build a model to make the diagnosis. **[14][**20]

*Figure 1 electronic imaging and metadata used for the analysis*

In coordination with the same, some of the studies with the different languages of the AI for the precise verification of the disease are as, Imani et al [**[15]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b21) develop a technique to detect the morphological component analysis (MCA) for exudates and blood vessel, in the same course Pavle used the CNN. Yazid et al [**[16]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b22) identified the hard exudation and optic disc base, while others reported that they used Lattice Neural Network with Dendritic Processing (LNNDP) enhancement techniques for the detection of blood vessels in retinal images.[**[17, 18]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b23) Akyol et al [**[19]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b25) work on auto-optic disc imaging on the bases of keypoint detection, texture analysis, and visual dictionary techniques. Niemeijer et al [**[20]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b26) work on optic disc imaging by combining k-nearest neighbour (kNN) and cues. [Fig-1](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/figure/ijo-11-09-1555-g002/)

The combined macular optical coherence tomography (OCT) with fundus image, identifies the sign of macular oedema. After all, a study has reported an algorithm can detect and quantify subretinal (blue colour) or intraretinal fluid (green colour). [Fig-2](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/figure/ijo-11-09-1555-g002/) [**[21]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b27) identifies age-related macular oedema (AMD), diabetic macular oedema (DME), and retinal vein occlusion (RVO).

*[Figure 2 Illustration of the automated detection of macular fluid in OCT](https://www.ncbi.nlm.nih.gov/core/lw/2.0/html/tileshop_pmc/tileshop_pmc_inline.html?title=Click%20on%20image%20to%20zoom&p=PMC3&id=6133903_ijo-11-09-1555-g001.jpg" \t "tileshopwindow)*

**RETINAL VEIN OCCLUSION:**

According to prevalence retinal vein occlusion (RVO) stepped second for the cause of blindness due to superficial haemorrhage, exudation, and retinal oedema. **[22]** If it has involved the macula, visual acuity decreases up to significant blindness. The people who are diseased are old aged having hypertension, arteriosclerosis or cardiovascular disease. **[23, 24]** The machine learning for RVO has low involvement but CNN accompanies patch-based and image-based mechanisms.

**MACULAR DEGENERATION:**

AI in coordination with optical coherence tomography (OCT) imaging becomes of immediate interest for age-related macular degeneration (ARMD) and other macular disorders. Two-dimensional imaging provides the anatomical state of the retina with the classification of diseases like choroidal neovascularization (CNV), macular oedema, drusen, geographic atrophy, epiretinal membrane (ERM), vitreomacular traction, macular hole, central serous chorioretinopathy (CSR), etc., along with the referral quality like urgent, semi-urgent, routine, or observational. **[25]**

**RETINOPATHY OF PREMATURITY:**

In childhood, retinopathy of prematurity is counted as the leading cause of blindness.**[26, 27]** Infants with pre-disease require regular observation and those who have advanced stage need treatment.**[28]** the application of AI improves patient care. The disease progression, regression, and response to treatment are based on the patient’s severity score.

The automatic identification of ROP for promised results focused on two-level classification (plus or not plus disease)[**[29-32]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b49). Homegrown 3 nethra camera (Forus Health Incorporated, Bengaluru, Karnataka, India) has also demonstrated high performance in accurately identifying the ROP stage in retinal images.**[33]**

**ANTERIOR SEGMENT DISEASES:**

Cataract and glaucoma are very common issues for the eye. [**[34,**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b55) **35]** Gao et al [**[36]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b57) proposed a system which automatically graded nuclear cataracts by slit-lamp imaging through CNN. Goh et al.**[**[**37**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R27)**]** explored the AI application for cataract screening with the help of ophthalmic fundus and slit lamp imaging to automate best-fit intraocular lens possibility.

 Wu et al.**[**[**38**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R28)**]** provided keratoconus identification,**[**[**39**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R29)**,** [**40**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R30)**]** and corneal power assessment after refractive surgery.**[**[**41**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R31)**]**through Scheimpflug camera.

Glaucoma damages the optic nerve and the diagnosis of glaucoma is based on the intraocular pressure, the thickness of retinal nerve fibre, the optic nerve and visual field examination [**[42, 43]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b62) thus early detection is very important as it can be slowed down the symptoms by reasonable treatment otherwise, the end stage of glaucoma causes irreversible blindness.**[44, 45, 46]** Deep Learning algorithms are capable to identify glaucoma through the optic disc and to recognize damage to the glaucomatous nerve fibre layer on wide-angle OCTs,**[**[**4**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R24)**7]** to justify earlier visual field loss. The prediction tool also helps for future possibilities of the disease.

Omodaka et al[**[48]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b64) introduce a machine-learning algorithm; the quantitative parameter, to classify the optic disc imaging for open-angle glaucoma with an accuracy of 87.8%.

The main theme for the glaucoma evaluation is based on access to input images of cup disc ratio **[49, 50]** grabbed by the fundus images, the visual field [**[51]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b67) or the thickness of retinal nerve fibre, examined by OCT [**[52]**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6133903/#b68).

**LIMITATIONS AND ETHICAL ISSUES:**

Although if the weaker training set of images and its quality is presented to the AI tool, it produces an unlikely accurate outcome because of reference slandered, so datasets should be well refined and could be maintained under certain limits. For example, the AI tool works well for diabetic retinopathy but it may get confused with the central retinal vein occlusion.

The CNN-based system analyzes an image or data on the bases of its own self-generated rules and the surety of outcome becomes troublesome to the observer, this issue is known as the black box problem. Thus if CNN evaluates any of the altered images, then it can result in disease-free.**[53]** The future aspects indicate some of the attempts at AI-based eyelid and periorbital measurements, to plan for the horizontal strabismus surgery.**[54]**

The following six ethical concerns identified by the WHO-

1. Protecting human autonomy,

2. Promoting human well-being and safety in the public interest,

3. Ensuring transparency, explainability, and intelligibility,

4. Fostering responsibility and accountability,

5. Ensuring inclusiveness with equity, and

6. Promoting responsive and sustainable AI.**[55]**

These ethical and legal key points were already emphasized by Gerke et al.,**[**[**5**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9240552/#R35)**6]** and advocated for a high level of public trust. The second issue is very unlikely to be developed whether ophthalmologists will be replaced by AI or a new race of patients will attend to the ophthalmologist/ optometrist, with referable or treatable disease. Here are the chances for a physician-based medical practice versus AI attraction, but AI could not cover the total skill although maximize the efficiency and precision of the diagnosis.

Finally, for any diagnosis machines can help but they cannot produce well enough medical decisions. Although in the future AI will occupy an effective role in medicine and in the current situation, AI has established a big role in research.

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