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A Overview of the State of Artificial Intelligence in Ophthalmology Today and Its Possibilities for the Future

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ABSTRACT:

A significant area of research in "computer science is artificial intelligence (AI)". Although AI has a wide range of medical applications, it will be especially useful in ophthalmology and will fundamentally alter how many eye disorders, including "corneal ectasias, glaucoma, age-related macular degeneration, and diabetic retinopathy", are diagnosed and treated. However, because AI has been predominantly developed as a branch of computer science, many medical experts are not conversant with its concepts and jargon. Deep learning and machine learning are two crucial but sometimes misunderstood words that are incorrectly used interchangeably. An overview of recent advancements in AI and ophthalmology is provided in this article.

Keywords: "artificial intelligence, deep learning, machine learning, ophthalmology, diabetic retinopathy".

INTRODUCTION:

A subject of computer science called artificial intelligence (AI) focuses on building machines that mimic human intelligence. These machines are capable of carrying out useful tasks including speech recognition, image recognition, and problem solving 2-4. Weak or narrow AI, which requires individual programmes to be developed for each task, is a current limitation of AI.

In this area of computer science, definitions are frequently ambiguous and used interchangeably. In this overview, artificial intelligence (AI) will be used to refer to the general idea of intelligent computers that can mimic human characteristics, including

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problem-solving. Below, we'll describe machine learning and deep learning as AI processes. To do a task in the past, a computer needed to be pre-programmed with a set of instructions or algorithms. This frequently gave the impression that the device was intelligent. The machine was merely obeying instructions; thus, it wasn't actually intelligent. These machines could only adapt in ways that the pre-programming had predicted and taken into account. Furthermore, because the machine was designed by humans, its capabilities were constrained by the level of technological sophistication of people who did the programming. When machines go through the machine learning process, they can develop their skills and learn much more efficiently to carry out a task.

Computer learning is an AI technique where a machine generates its own code and learns to finish a task on its own. The term was first used by Arthur Samuel in 1959. Giving someone a task to accomplish, such as binary task of dividing fundus pictures into “diabetic retinopathy (DR) and non-DR”, is the initial step in this procedure. The machine will need a sizable collection of fundus images to “learn from (training dataset), as well as a separate database for validation”, to finish this assignment (validation dataset). Experts will need to spend a lot of time precisely labelling each image with the appropriate grouping of DR or non-DR in this situation. Following that, a fundamental learning structure for algorithms, such as a support vector machine or neural network, is selected.

Accepted Article network, which is frequently determined by testing on smaller quantities of data or by information from other studies (common structure chosen and explored in more detail later). The training data is subsequently provided to the machine, which then generates its own responses.

The computer then compares its results to those that are accurate. The machine reevaluates its methods and modifies its internal changeable parameters (weights) if its solutions have a high mistake rate, frequently learning one feature from the image at a time.

These changeable weights may number in the hundreds of millions in a typical system. The same training data is then re-fed to the system, which subsequently generates a fresh set of responses. This cycle repeats endlessly until the target output is attained or the results approach a plateau. For evaluations of “external validity, the final sensitivity, specificity, and accuracy ratings can be compared with the validation dataset”.

In the prior case, a supervised machine-learning model was used, in which the computer learns from data that contains only accurate responses. Supervised learning is frequently helpful for categorization (may be continuous variables like height or weight, or categorical values like "illness" or "no disease") 7. Unsupervised machine learning frequently entails examining data for which there are no clear answers, with the underlying objective being to model the data's distribution or structure in order to understand it better. Finding correlations using this is advantageous. 7. There are more categories within machine learning. Deep learning is a branch of machine learning that makes use of the structure of an “artificial neural network (ANN)". The biological neural network served as an inspiration for ANNs. Continuous variables like height or weight are fed into numerous layers of neurons that have been formed through a machine-learning process in an ANN. 7. Each layer in an ANN learns various features with various weightings for various inputs. This enables the machine to adapt and carry out challenging tasks. The ANN is known as deep learning because of the several layers. The use of the heavy side function, which generates an all-or-nothing response comparable to nerve firing, gives some ANNs their second major similarity to biological neurons. For instance, the heaviside function turns a negative input to a zero, which prevents the neuron from transmitting information when the input to each layer is paired with the weighting is negative. The neuron transmits the information if the outcome is positive since the heavyside function changes the result to a 1 in that case.

There are so many opportunities to use AI in medicine that some physicians worry about being replaced by machines. Since weak AI has made the most progress to date, it is doubtful that AI will eventually replace the majority of medical specialists.

However, deep learning will be a beneficial tool for helping doctors with their clinical practise because of its ability to learn features from enormous amounts of data and to self-correct to increase its accuracy.8. Additionally, integrating the strengths of deep learning algorithms and human clinicians should lessen the inherent flaws in diagnostics and treatment in our existing system 9,10. The heaviside function, however, turns the result to a 1 and the neuron passes that if it is positive. Finally, Additional uses for AI's predictive powers in medicine will emerge, particularly in the areas of health risk alarms and health outcome forecasts 11.

AI will increasingly be incorporated into our medical technology in the future. "Currently AI tools are being utilised in fields such as cancer, neurology and cardiology" [8,12,13]. We estimate tremendous advancements in the field of medical imaging as a result of deep learning's special propensity for image processing.

Currently, single pictures like x-rays or photos of skin lesions are particularly well-suited for deep learning. We will be able to include AI evaluations into complex multi-image datasets like magnetic resonance imaging and computed tomography scans as our technology and algorithms advance. This paper specifically examines the state of AI in ophthalmology today.

METHODS AND MATERIALS:

In May 2018, a literature review was carried out. MEDLINE and Scopus were the two databases that were used in the literature search. Artificial intelligence search terms were used to do independent searches for each specific condition. Artificial intelligence and the following search terms were used: "artificial intelligence AND ophthalmology, artificial intelligence AND keratoconus, artificial intelligence AND glaucoma, artificial intelligence AND diabetic retinopathy, artificial intelligence AND macular degeneration, artificial

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intelligence AND cataract, artificial intelligence AND retinopathy of prematurity". There were no extra restrictions on the keyword searches because it was anticipated that each subject would have a limited amount of material. English-language full articles and abstracts were included. Peer-reviewed journal articles that enhanced our knowledge of artificial intelligence in ophthalmology and were pertinent to the article's goal were chosen for inclusion in this review. Additionally, publications that were pertinent to our subject and located in the references were chosen.

COMBATING CORNEAL CONDITIONS

A bilateral, irreversible disorder known as keratoconus causes the cornea to weaken, protrude, and scar over time. Except in extremely exceptional circumstances, many people initially only have unilateral traits that develop into bilateral ones through time 15. The condition progresses to an advanced stage at which refractive correction is quite challenging. In order to improve eyesight at this time, corneal transplantation is frequently advised 16.

Studies have shown that treatments such intra-corneal ring implantation and corneal collagen cross-linking are efficient substitutes for transplants, stabilising the condition over the "long term with follow-up of up to 10 years 17–19". The importance of early identification of corneal ectatic illness cannot be overstated, though, as these treatments stop the disease's progression. Research into early identification of keratoconus offers essential information for treating various corneal ectasias in addition to improving the prognosis for those who have the condition. This is especially relevant to refractive surgeons who do LASIK because iatrogenic corneal ectasia following LASIK is one of the most dangerous side effects 20, 21. Researchers have spent a lot of time and effort creating accurate diagnostic techniques to find people who have sub-clinical signs of corneal ectasia because the issue is permanent and impairs the person's visual prognosis 22, 23. However, it is still very difficult to recognise subclinical corneal ectasia.

The ophthalmologist can obtain a lot of intricate information about each cornea through topography and tomography. In spite of this, it might be quite difficult for an ophthalmologist to tell the difference between subclinical and normal keratoconus in the majority of the measures evaluated 24. Optometrists' individual interpretations of patterns or empiric cut-off values, which vary from machine to machine, frequently influence their decision. This process takes a lot of time and is unreliable. Recent studies have shown how AI can offer a different approach to identifying the patients who are most at risk 23.

Research on corneal ectasia first concentrated on creating a method for separating overt abnormalities in the cornea from normal corneas, such as keratoconus, as well as other modifications including astigmatism and photorefractive keratectomy, using information from the Orbscan IIz. Because they offered posterior topographical data in addition to the normal anterior information, results from the Orbscan IIz were preferred over data from other devices in earlier studies. Souza et al. evaluated the performance of support vector machine,

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multiple layer perceptron classifiers, and radial basis function neural networks utilising Orbscan IIz data; none of them significantly outperformed the others in identifying the aforementioned corneal abnormalities ("Area Under the Curve of the Receiver Operating Characteristic [AUROC]: 0.98-0.99; sensitivity 0.98-1.00; specificity 0.98-1.00"). It's interesting that the AUROC of the MLCs were higher than those discovered while assessing each feature for diagnosing corneal disorders separately. In order to distinguish keratoconus from normal eyes, Smadja et al. (2013) and Hidalgo et al. (2016) discovered that their respective MLCs were extremely sensitive and specific ("Smadja et al.: 0.993 sensitivity, 0.995 specificity; Hidalgo et al.: 0.991 sensitivity, 0.985 specificity, 0.998 AUROC") 23,24. In the end, these MLCs have discriminating skills that are comparable to those of specially created non-AI indexes like the Cone Location and Magnitude Index 28 and the Klyce/Maeda Keratoconus Index 27. In comparison to data from the Orbscan IIz, Scheimpflug tomography data were preferred after Smadja et alinvestigation .'s in 2013. Scheimpflug tomography-based devices created three-dimensional reconstructions of the anterior segment using a non-contact manner 23,24, which provided the data for the subsequent comparisons. The anterior and posterior surface topography of the Scheimpflug tomography data were regarded to be superior to that of the Orbscan IIz because they were obtained from actual elevation measurements rather than mathematically, which is supposed to overestimate the elevation of the posterior curvature. 33 After machine learning effectively differentiated overt corneal abnormalities, research focused on developing artificial intelligence (AI) that may assist in identifying sub-clinical features of corneal ectasia. In order to achieve this, researchers compared people with unilateral features of keratoconus (subclinical keratoconus) to people without corneal disease using topographical and tomographic data from the "normal" eye. Both Arbelaez et al. and Smadja et al. showed that AI is capable of recognising the characteristics of subclinical corneal ectasia in eyes 23. In a sizable investigation, Arbelaez et al. attempted to employ an MLC to distinguish between normal eyes and subclinical keratoconus. 3502 eyes (877 keratoconus eyes, 426 sub-clinical keratoconus eyes, 940 abnormal eyes, and 1259 normal eyes) were used to train an MLC. The instrument detected subclinical keratoconus with 0.973 accuracy, 0.920 sensitivity, and 0.977 specificity.

The prototype developed by Smadja et al. was tested on 372 eyes (197 patients) distributed among three However, it is challenging to draw judgments about the usefulness of each software when the researchers did not test and evaluate it using fresh data samples. Individuals who displayed early keratoconus-like ectasia characteristics rather than subclinical keratoconus were included in the subclinical keratoconus groups in both studies, which may have given the results a false impression of accuracy 23,24. Hidalgo et al. created the keratoconus helper in response to this, intending to instal it with Pentacam software to enable real-time evaluation of measured data. 24, 31, 860 eyes were utilised to train an MLC for this software, including 194 normal, 28 astigmatic, 117 post-refractive surgery, 67 subclinical keratoconus, and 454 keratoconus eyes. By the end of training stage 24, their MLC had a 0.922 AUROC, 0.791 sensitivity, and 0.979 specificity for identifying normal

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eyes from subclinical keratoconus. It is thought that the stricter classification of sub-clinical keratoconus is what caused the poorer sensitivity shown in this study (participants with any symptomatic signs were excluded from the subclinical keratoconus group). After their initial study, Hidalgo et al. carried out a validation study in which they assessed their keratoconus assistant against seven additional indices from the literature and an independent evaluation by qualified clinical clinicians at the Rothschild foundation (RF) and Antwerp University Hospital (UZA) 31. The keratoconus assistant was found to agree well with RF and UZA classifications; nevertheless, it caused a high number of false positives, labelling 31/61 Rothschild normal participants and 23/44 UZA people as suspect for subclinical keratoconus. In the forthcoming version of the programme, Hidalgo et al. suggested that the sample size of the training set be increased, especially for the suspect group, to reduce the number of false-positives 31. To improve the accuracy of the aforementioned AI, more study has been done. In attempt to increase the accuracy of identifying sub-clinical corneal ectasia by analysing bilateral data, Kovacs et al. analysed 60 eyes from a group of keratoconus patients and compared them to 15 normal colleague eyes of patients with unilateral keratoconus symptoms. In this work, intra-patient corneal asymmetry (bilateral index of height decentration) was specifically connected to a significant improvement in the classifier's performance when compared to unilateral data when the MLC was trained using the index of height decentration. This indicates that a decline in between-eye similarity should be taken into account as a potential indicator of ecstatic illness, and this trait might be added to decision engines in the future to identify early keratoconus 30. Ambrosio et al. recommended utilising a Tomographic and Biomechanical Index (TBI) that integrated Scheimpflug-based corneal tomography (Pentacam HR) and biomechanical analysis (Corvis ST tests) 29 to further improve corneal detection.

They conducted a retrospective study on 850 eyes with keratoconus 29 (one randomly selected eye from 480 normal people, one randomly selected eye from 204 patients, 72 eyes affected with unilateral keratoconus, 72 eyes sub-clinically related to the previous group, and 22 eyes removed).

For detecting subclinical corneal ectasia using the TBI, they had a 0.904 sensitivity and a 0.04 false positive rate with an optimization cut-off value set to 0.29 (0.96 specificity; AUROC 0.985). Ambrosio et al. also tested random forests, support vector machines, and forward stepwise inclusion again, with the latter strategy being the most accurate for creating TBIs.

GLAUCOMA GAUGE

The chronic progressive optic neuropathy known as primary open-angle glaucoma (POAG) is characterised by typical visual field degradation and increases in intraocular pressure (IOP) 34. Without prompt detection and care, POAG can result in permanent visual loss 34. As a result, it is crucial to test for and monitor for POAG. A significant risk factor for POAG is

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increased IOP. IOP measurements at vision exams are typically used for screening in a population that is otherwise asymptomatic. Although their IOP is modest, some patients nevertheless improve and develop POAG. Therefore, serial stereoscopic optic disc pictures (SODP), standard automated perimetry (SAP), or OCT imaging can also be used to detect higher risk patients. When POAG is identified, it is followed up with routine clinical exams as well as monitoring for SODP, SAP, IOP, and OCT 35. Ideally,

AI would use screening and monitoring datasets to create efficient decision support systems that are as sensitive and specific as or better than the methods now in use.

One of the first AI studies to use a variety of MLCs and independent factors to examine POAG progression in 180 individuals (73 stable eyes, 107 glaucoma advanced) was published in 2013 by Yousefi et al. 35. They discovered that in an early-moderate stage of the disease, retinal nerve fibre layer (RNFL) characteristics by themselves were sufficient to inform MLCs to distinguish between stable and progressing POAG. Additionally, they discovered that adding SAP to RNFL data did not enhance MLC performance or accuracy in detecting POAG progression, and that MLC performance was noticeably lower when SAP was employed alone compared to RNFL results.

The most sensitive MLCs ("Random Forest tree: sensitivity 0.82, specificity 0.74, AUROC 0.87; Lazy K star: sensitivity 0.80, specificity 0.73, AUROC 0.88") were random forest tree and lazy K star. The development and validation of an ANN model to distinguish POAG from POAG suspect without a visual field test was completed two years later by Oh et al. The ANN model was created using data from 257 participants, and its capacity to predict POAG 36 was tested using data from the remaining 129 participants. "The most discriminatory model was their ANN model with nine factors in non-categorised form (validation: sensitivity 0.783, specificity 0.859, AUROC 0.890). Sex, age, menopause, duration of hypertension, spherical equivalent refractive error, IOP, vertical cup-to-disc ratio, and superotemporal and inferotemporal cup abnormalities were all helpful in differentiating patients". This study offered potential helpful data-points to take into account in future studies and illustrated the potential capabilities of ANNs in POAG diagnosis. The implementation of such a programme might be ineffective as a result of the lengthy time it took to collect the data points for this study, some of which required ophthalmologist evaluation. As a result, the conclusions of this study have limited real-world implications.

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implications. Since then, countless further efforts have been made using a variety of various methods to differentiate POAG from normal. Three studies examined the use of CNN 38–40 to identify POAG on fundus imaging. Both Kim et al. and Raghavendra et al. concentrated solely on distinguishing between glaucoma and normal fundus images. Kim et al. used 540 POAG and 540 regular fundus pictures to train its MLC. The goal of this study was to ascertain whether preserving high-resolution images with a red, green, and blue colour scheme when learning from the images provided any additional benefits. When the original centre-cropped image of the optic disc was used instead of cropped down-sized images (with accuracies as low as 65.2%), Kim et al. reported accuracy as high as 87.9%. This shows promise for this method 40 and is nearly similar to the accuracy of human experts (reported at around 80%). Raghavendra et al. acquired a score of 0.98 for sensitivity, specificity, and accuracy after training their MLC on 589 normal and 837 glaucoma pictures. They understood that while better resolution photos could make it possible to detect subtle variations, the computational time would be greatly increased. The demographic information from the dataset must be used to externally validate the outcomes of this technique. Last but not least, Ting et al. also sought to identify age-related macular degeneration and DR while also attempting to identify glaucoma (AMD). A total of 494 661 fundus pictures were used to train Ting et alMLC; .'s 125 189 of them were referrable POAG 38. Due to the fact that these fundus photos were taken from a multiethnic community, the external validity may be increased

With a sensitivity of 0.964 and a specificity of 0.872, the MLC's AUROC for POAG was 0.942. These results show promise for possible clinical decision assistance software when compared to human clinician accuracy scores, especially when taking into account the usefulness of being able to recognise numerous distinct common conditions for referral.

There may be additional methods for POAG detection. Data from OCT and SAP investigations is also included, along with hybrid machine learning that combines a CNN and numerous MLCs. The outcomes of these investigations can be used to potentially enhance CNN results when combined with fundus pictures in a hybrid strategy.

ASSESSMENT OF AGE-RELATED MACULAR DEGENERATION:

One of the main factors contributing to irreversible sight loss in the ageing population is age-related macular degeneration (AMD). To create management strategies that are unique to each patient's needs, doctors must accurately identify AMD. AI could be used to support decision-making in order to improve this.

The screening process has advanced significantly. A diagnostic technique for detecting common curable retinal illnesses, such as diabetic macular oedema (DME) and age-related macular degeneration (AMD), was created by Kermany et al. 108312 photos from 4686 patients were used by his team to train the MLC, and a separate 1000 images from 633 patients were used to verify its functionality. The MLC categorised the disorders into

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categories based on how urgently the patient needed to be referred, such as choroidal neovascularization and DME, and categories based on how routinely the patient needed to be referred, such as drusen as part of dry AMD. The MLC classified retinal diseases with a sensitivity of 0.978, specificity of 0.974, and AUROC of 0.999. The performance of the MLC was statistically comparable to that of human experts. To distinguish between normal and AMD OCT pictures, Lee et al. have created an AMD screening system 47. On 48 312 normal and 52 690 AMD pictures, they trained their MLC. Their MLC had an AUROC of 0.9746 and a maximal sensitivity and specificity of 0.926 and 0.937, respectively. Ting et al. sought to distinguish between DR, POAG, and AMD as was previously explored in the context of glaucoma. In this study, the MLC was trained using 72,610 photos of referrable AMD, and it was validated using 35948 images of referrable AMD. Their MLC was capable to diagnosing AMD with an AUROC of 0.931, a sensitivity of 0.932, and a specificity of 0.887. Some studies have also looked at reduced sample sizes to prevent over-fitting. With a sensitivity of 1.00 and a specificity of 0.92, Treder et al. employed OCT imaging (1112 pictures) to develop an MLC that distinguishes between a healthy macula and one with exudative AMD. All of these investigations employed a CNN variant, which is effective at categorising images because the input is evaluated at the pixel level 38. Ultimately, it seems that an MLC developed using a CNN could be a beneficial approach for screening for AMD because the MLCs perform at a level comparable to professional graders.

Some research have concentrated on assessing AMD and forecasting visual acuity from OCT scans in addition to screening. This will boost clinicians' decision-making and assist them in developing a visual prognosis. MLCs that could gauge visual acuity were created by Aslam et al. and Schmidt-Erfurth et al. Aslam et al. trained their

DIAGNOSING DIABETIC RETINOPATHY:

A primary contributor to visual impairment globally, diabetic retinopathy (DR) is expected to become more common as the population ages and obesity becomes more common. AI integration into DR screening and surveillance systems may help boost DR management effectiveness. Numerous studies have examined AI tools that can recognise and even classify fundoscopic images with DR. In these experiments, MLCs have already demonstrated their ability to distinguish DR from non-DR images and classify them.

This has led to the creation of a few notable AI MLCs that exhibit classification outcomes comparable to those of trained graders and ophthalmologists 3. The MLCs were generated for each study using sizable datasets. A total of 118 419 images were used by Gulshan et al. for training, including 53 759 normal images and 64 660 DR images (divided into DR categories mild, moderate, severe, and proliferative); additional categories included referable DME and referable DR within the same dataset but apart from the other classification. 3.

Ting et al. trained on 494 661 retinal images, of which 76 370 were DR images while the remaining 38 were normal, glaucoma, and AMD images. Finally, Gargeya et al. trained an AI

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model to distinguish between diabetic and healthy fundi using 75 137 fundus pictures. The sensitivity and specificity for referable DR over the two validation datasets were 0.870-0.903 and 0.981-0.985, respectively, according to Gulshan et alMLC, .'s which had an AUROC of 0.990-0.991. 3. In contrast to Gargeya et alMLC, .'s which had an AUROC of 0.97 for detecting referable DR on validation (sensitivity and specificity for referable DR were 0.94 and 0.98, respectively), Ting et alMLC .'s had an AUROC of 0.936 for referable DR (sensitivity and specificity of referable DR were 0.905 and 0.916). The inability to identify specific indications by severity and the potential for limited detection of DME without OCT input were limitations of these research. There is currently ongoing investigation into sign detection 62. Despite these drawbacks, the findings imply that it would be possible for current or future MLCs to be used in clinics as screening and computer-aided diagnostic tools. Future studies should concentrate on examining these MLCs in clinical contexts.

OTHER AI OPHTHALMOLOGY RESEARCH

Early ophthalmology research has made use of AI in other fields. Confocal imaging was used in one study to categorise corneal images. Another study examined the use of contact lenses to detect Staphylococcus aureus non-invasively. While some research is focused on improving AI technology for future use, such as improving AI recognition of the optic nerve head 70 or improving the false positive or negative rates from imbalanced datasets, other studies have examined ophthalmological conditions such as cataracts and retinopathy of prematurity. It's interesting to note that some research are applying the ophthalmic datasets to other areas of health. At the end of the day, AI is being studied for its advantages in a wide range of applications in ophthalmology and beyond.

FUTURE CHALLENGES

There are difficulties in ophthalmology AI research. The calibre of the datasets used to train and validate an AI software determines its capabilities. Predicting the number of training photos needed in a dataset can be difficult because it is human nature to believe that the more images, the better. The training procedure is less effective when there are too many datasets, and the MLC may end up being overfit to the training dataset. For increased external validity, the dataset should include include photographs from a diverse demography. It is important to remember that algorithms could not be universally applicable and that devices from different brands may have small variations that affect the assessments' accuracy. Additionally, limiting the number of categories inside a programme to those that have significant prognostic importance can help reduce dataset size and algorithm complexity.

Research in AI is a complicated area. This is due to the fact that it naturally combines two otherwise distinct fields of knowledge: computer science and medicine. The needs of that specific readership are the main emphasis of research presented in one area of science. This implies that the other discipline might be overlooking information and findings that could be

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very helpful, which is a significant inefficiency. In order to reduce the variation between studies, it is critical that future research establish a standard for reporting.

Future problems from commercialization of AI will also arise. AI MLCs will probably be supplied alongside and for use with specific medical technology. Conflicts of interest should be anticipated, and possible safeguards should be taken when working with medical companies that have a financial stake in the outcome. If AI does advance medical care, it will be crucial to share those advancements with people that cannot afford them. Due to competing financial interests of medical companies, it will probably be up to healthcare professionals to advocate for this.

CONCLUSION:

AI will be a disruptive technology. In order to improve patient care, it is critical to research and evaluate the prospective applications of this new technology. Future computer-aided diagnosis and management systems may incorporate AI programmes. When determining the necessity for referral outside of ophthalmology, triage methods may be helpful in a primary care context. This could be especially helpful in rural areas where access to and availability of essential services may be restricted. It may be beneficial to boost assessment efficiency in ophthalmology so that more time to engage with patients if they choose. It's crucial to keep in mind that AI systems might also be dangerous. In the event that unneeded screening takes place, there is a chance for overdiagnosis. Furthermore, it could be problematic if the diagnostic software is released directly to patients as the potential opportunities and risk of AI could be magnified .

REFERENCES:

1. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA 2016; 316: 2402–10.
2. Bordes A, Chopra S, Weston J. Question Answering with Subgraph Embeddings [Internet]. arXiv [cs.CL]. 2014. Available from: http://arxiv.org/abs/1406.3676
3. Samuel AL. Some studies in machine learning using the game of checkers. IBM J Res Dev 2000 ; 44: 206–26.
4. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;52: 436–44.
5. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: past, present and future. Stroke Vasc Neurol 2017 ;2:230–43.
6. Dilsizian SE, Siegel EL. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. Curr Cardiol Rep 2014;16: 441.
7. Patel VL, Shortliffe EH, Stefanelli M, et al. The coming of age of artificial intelligence in medicine. Artif Intell Med 2009; 46: 5–17.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11, S Iss 2, 2022

8. Neill DB. Using artificial intelligence to improve hospital inpatient care. IEEE Intell Syst 2013; 28: 92–5.
9. Thompson RF, Valdes G, Fuller CD, et al. Artificial intelligence in radiation oncology: A specialty-wide disruptive transformation? Radiother Oncol [Internet]. 2018 Jun 12; Available from: http://dx.doi.org/10.1016/j.radonc.2018.05.030
10. Krachmer JH, Feder RS, Belin MW. Keratoconus and related noninflammatory corneal thinning disorders. Surv Ophthalmol 1984; 28: 293–322.
11. Alfonso JF, Lisa C, Merayo-Lloves J, Fernández-Vega Cueto L, Montés-Micó R. Intrastromal corneal ring segment implantation in paracentral keratoconus with coincident topographic and coma axis. J Cataract Refract Surg 2012; 38: 1576–82.
12. Wollensak G, Spoerl E, Seiler T. Riboflavin/ultraviolet-a-induced collagen crosslinking for the treatment of keratoconus. Am J Ophthalmol 2003; 135: 620–7.
13. Mazzotta C, Traversi C, Baiocchi S, et al. Corneal Collagen Cross-Linking With Riboflavin and Ultraviolet A Light for Pediatric Keratoconus: Ten-Year Results. Cornea 2018; 37: 560–6.
14. Pramanik S, Musch DC, Sutphin JE, Farjo AA. Extended long-term outcomes of penetrating keratoplasty for keratoconus. Ophthalmology 2006; 113: 1633–8.
15. Smadja D, Touboul D, Cohen A, et al. Detection of subclinical keratoconus using an automated decision tree classification. Am J Ophthalmol 2013; 156: 237– 46.e1.
16. Hidalgo IR, Rodriguez P, Rozema JJ, et al. Evaluation of machine-learning This article is protected by copyright. All rights reserved. classifier for keratoconus detection based on scheimpflug tomography. Cornea 2016; 35: 827–32.
17. Maeda N, Klyce SD, Smolek MK, Thompson HW. Automated keratoconus screening with corneal topography analysis. Invest Ophthalmol Vis Sci 1994; 35: 2749–57.
18. Kawamorita T, Uozato H, Kamiya K, et al. Repeatability, reproducibility, and agreement characteristics of rotating Scheimpflug photography and scanning-slit corneal topography for corneal power measurement. J Cataract Refract Surg 2009; 35: 127–33.
19. Yousefi S, Goldbaum MH, Balasubramanian M, Jung T-P, Weinreb RN, Medeiros FA, et al. Glaucoma progression detection using structural retinal nerve fiber layer measurements and functional visual field points. IEEE Trans Biomed Eng 2014;61 : 1143–54.
20. Oh E, Yoo TK, Hong S. Artificial Neural Network Approach for Differentiating Open-Angle Glaucoma From Glaucoma Suspect Without a Visual Field Test. Invest Ophthalmol Vis Sci 2015; 56: 3957–66.
21. Raghavendra U, Fujita H, Bhandary SV, Gudigar A, Tan JH, Acharya UR. Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images. Inf Sci 2018; 441: 41–9.

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22. Bogunovic H, Montuoro A, Baratsits M, et al. Machine Learning of the Progression of Intermediate Age-Related Macular Degeneration Based on OCT Imaging. Invest Ophthalmol Vis Sci. 2017; 58: BIO141–50.
23. Kermany DS, Goldbaum M, Cai W, et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell 2018 ;172: 1122–31.e9.
24. Lee CS, Baughman DM, Lee AY. Deep Learning Is Effective for Classifying Normal versus Age-Related Macular Degeneration OCT Images. Ophthalmology Retina 2017 ; 1: 322–7.
25. Treder M, Lauermann JL, Eter N. Automated detection of exudative agerelated macular degeneration in spectral domain optical coherence tomography using deep learning. Graefes Arch Clin Exp Ophthalmol 2018; 256: 259–65.
26. Aslam TM, Zaki HR, Mahmood S, et al. Use of a Neural Net to Model the Impact of Optical Coherence Tomography Abnormalities on Vision in Age-related Macular Degeneration. Am J Ophthalmol 2018; 185: 94–100.
27. Safi H, Safi S, Hafezi-Moghadam A, Ahmadieh H. Early detection of diabetic retinopathy. Surv Ophthalmol [Internet]. 2018 Apr 19; Available from: http://dx.doi.org/10.1016/j.survophthal.2018.04.003
28. Raju M, Pagidimarri V, Barreto R, Kadam A, Kasivajjala V, Aswath A. Development of a Deep Learning Algorithm for Automatic Diagnosis of Diabetic Retinopathy. Stud Health Technol Inform 2017; 245: 559–63.
29. Xu K, Feng D, Mi H. Deep Convolutional Neural Network-Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image. Molecules [Internet]. 2017 Nov 23;22(12). Available from: http://dx.doi.org/10.3390/molecules22122054
30. Sharif MS, Qahwaji R, Ipson S, Brahma A. Medical image classification based on artificial intelligence approaches: A practical study on normal and abnormal This article is protected by copyright. All rights reserved. confocal corneal images. Appl Soft Comput 2015; 36: 269–82.
31. Veli M, Ozcan A. Computational Sensing of Staphylococcus aureus on Contact Lenses Using 3D Imaging of Curved Surfaces and Machine Learning. ACS Nano 2018; 12: 2554–9.
32. Gao X, Lin S, Wong TY. Automatic Feature Learning to Grade Nuclear Cataracts Based on Deep Learning. IEEE Trans Biomed Eng 2015; 62: 2693–701.