A review on contact lens inspection

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ABSTRACT

Over the year, contact lens detection has attracted attention and interest from many researchers to study further in this field of inspection. This paper provides a comprehensive review of the existing literature surrounding contact lens inspection methods. In this paper, contact lens-related, defects-related, and inspection methods related are described in detail. To detect contact lenses in a single image and also multi-image, numerous techniques have been developed and this paper is aimed at classifying and evaluating these algorithms. Also, contact lens inspection based on conventional and artificial intelligence methods will be discussed in detail. The industrial production process of contact lenses probably needs to be constructed with advanced tools based on recent technologies so that they can help in the inspection system to achieve accurate results of the inspection and reduce processing time.

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1. INTRODUCTION

Contact lenses are now widely used among us, allowing the country to develop a thriving sector. By 2020, the global contact lenses market is predicted to grow by 6.7% to $12,476.3 million US dollars [1], [2]. Hard and soft contact lenses are the two types of contact lenses available on the market. Hard contact lenses made of plastic were first developed in the mid-1900s. Due to long-term irritation of the eye surface, it can only be used for a short period. Gas-permeable rigid contact lenses were developed in the 1970s, allowing considerable amounts of oxygen to be passed to the corneal surface. Soft contact lenses, also known as hydrogel lenses, were designed in the 1970s [3] in response to some of the drawbacks of hard lenses. They make it more comfortable by allowing oxygen to reach the surface of the eye. Their small size makes them difficult to lose is one of the advantages of these contact lenses [4].

Hard contact lenses are made of a plastic called polymethylmethacrylate (PMMA), which is no longer widely used. Since oxygen cannot pass through PMMA contact lenses, they must be made small. Wearing contact lenses with improper care can lead to infections and consequences such as keratitis, corneal irritation, pain, redness, vision loss, and inflammation. Soft contact lenses are very comfortable and are manufactured from a flexible hydrophilic or advanced silicone-hydrogel material. These lenses have a high permeability of oxygen and are available in a variety of designs with some delivering more oxygen than others [5]. Myopia, hyperopia, presbyopia, and astigmatism are all corrected using soft contact lenses. Soft lenses are comfortable for the patient and feature a wide spherical and toric power range. Depending on keratometry data, the base curve of these lenses is either flat or steep [4], [5].

The production of soft hydrogel lenses has become significant for understanding the mechanical properties of both hard and soft materials. It became immediately apparent that soft lenses provided greater comfort than hard lenses. A wider range of physiological responses could be created by physically connected contact lens components, such as lens shape, surface defects, and especially edge-related effects, than the modulus itself [6]. By the 1980s, the combination of siloxymethacrylates and methyl methacrylate had resulted in a new generation of contact lens gas-permeable materials. The surface hardness of many of the newly created siloxymethacrylate gas permeable lenses was inadequate, resulting in surface scratches and, in some cases, film deposits were formed [7]. Soft lenses are made of hydrogel, a type of polymer that gives them their softness and flexibility. The major significant difference between hydrogels and other polymers is the hydrophilic structure that allows them to absorb a substantial amount of water, allowing for biocompatibility and customized mechanical strength [8]. Soft lenses adapt to the shape of a user's eye significantly more quickly than hard lenses due to their flexibility. Soft contact lenses can be disposed of once a day, once a week, or once a month. Contact lenses can also assist with everything from corrective vision and rehabilitation to cosmetic beauty. These applications suit the end user's requirements, such as lens wear life, comfort, dependability, handling skill, visual stability, and so on. This also ensures that contact lens applications meet the manufacturer's needs, such as material costs, ease of production, and contact lens durability [9]. Based on their appearances, contact lenses can be soft (or plain) or cosmetic (textured or colored). Because soft lenses are transparent, determining their presence was a bit difficult. These are commonly used to correct vision problems instead of spectacles. Cosmetic lenses, on the other hand, are frequently colored and have random textures imposed on them, making them easier to spot [10]. As people's interest in visual appeal has grown, more people are opting for contact lenses rather than glasses. However, because soft contact lenses come into direct contact with the eyes, foreign substances or microscopic flaws can cause eye damage, causing discomfort [11].

Lathe cutting, spin casting, and cast moulding are the three main procedures used to make soft contact lenses. The anhydrous polymer is initially shaped into tiny buttons with a specified diameter using a lathe. The first surface of the lens is curvaceously cut using a lathe tool. The button is transferred to a different lathe to be cut on the other side after one side has been finished. Before the lens is soaked in saline solutions to hydrate it, both sides are carefully polished to remove any edges. Next, spin casting uses centrifugal force to create contact lenses rather than cutting them mechanically. The polymerization process is started by either heat or ultraviolet (UV) light when the mould rotates at a steady pace. Cast moulding is the main used method for creating soft lenses. The anterior and posterior moulds are the two basic components of the moulding. A curved lens is created by pouring monomer into the posterior mould and then sealing it with the anterior mould. As the mould moves along the production line and the lens hardens, UV light initiated the polymerization process. The lens is thoroughly examined, hydrated, and prepared for packaging [12]. To satisfy the growing demand, manufacturers must produce contact lens rapidly. Due to the transparency of the materials used to make contact lenses, machine vision-based inspection was challenging, and typically inspection performed by humans. Additionally, contact lenses are subjected to a full inspection as opposed to a sampling inspection, which is more typical for most other products. Inspectors must check about 4,000 small contact lenses visually per day due to large-scale production and rapid inspection, in addition to 100% full inspection, which keeps false discovery and missed detection rates high [13]. This review aims to explore optical defects in contact lenses and related inspection methods that may contribute to the methods of contact lens detection. We will also analyze traditional methods and recent technology methods in the defect inspection of contact lenses. The paper is organized as: section 2, a brief review of the types of defects found in the contact lenses is presented. In section 3, the conventional inspection and artificial intelligence approaches for contact lenses are directly explained. Summary of past studies related to the contact lens inspection approaches is presented in table form in section 4. Finally, the conclusion of this review paper is outlined in section 5.

2. TYPE OF DEFECTS IN CONTACT LENS

In a recent issue, in the manufacturing industry of contact lenses, various types of optical defects occur under the contact lenses such as hardened lens surfaces, air bubbles, scratches, foreign particles, edge defects, and so on. Thus, these defects give an impact on the end-user in blurry vision and discomfort. In the production of plastic lenses, casting or injection procedures are applied. During the casting process, two pairs of moulds are filled with a liquid monomer, such as CR-39 or allyl diglycol carbonate (ADC), and the polymerization to cure the plastic is finished in the oven at a specific temperature and duration [14]. Circle and line defects were commonly found during the casting process. Normally, operators use a polarization technique, which involves placing the lens between two crossed polarizers, to check for lens defects. Operator skill was needed to make sure that all defective lenses were discarded [15].

Air bubbles, foreign matters, contamination, and scratches are some examples of defects in lenses. According to the study [16], there are some major defects found in the contact lens as shown in Figure 1. On the other hand, Figure 2 shows normal and cosmetic contact lens images with several types of defects which are cracks on the edge, small and big size bubbles, and edge defects. Figure 2(a), Figure 2(b), and Figure 2(c) demonstrate small and large bubble defects at the edge of normal contact lens images. While, Figure 2(d), Figure 2(e), and Figure 2(f) demonstrate the edge defects in cosmetic contact lens images.

Before applying a few inspection techniques, skilled workers inspected visually the lens defects on the production line. Human error is possible due to human limitations. A few automated inspection techniques were used instead of a manual inspection system to make sure that human decisions were accurate, minimizing human error and improving performance [16].

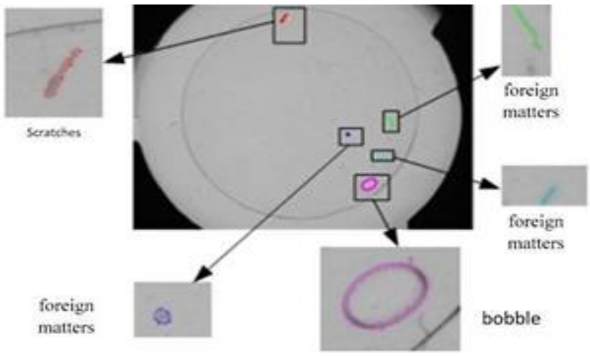

Figure 1. Some of the major defects were found in contact lenses [16]

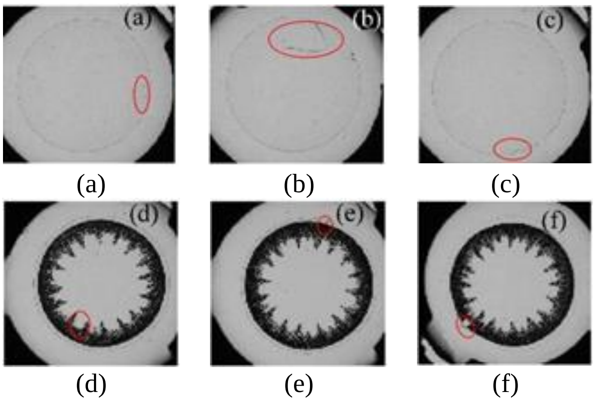

Figure 2. Some defects were found in (a) to (c) normal contact lens and (d) to (f) cosmetic contact lenses [16]

3. CONTACT LENS INSPECTION METHODS

In this section, some relevant studies are reviewed on several contact lens inspection methods based on traditional and artificial intelligence methods. The division of contact lens inspection methods is summarized in Figure 3. These approaches are divided into four categories: hardware-based, image processing, machine learning, and deep learning.

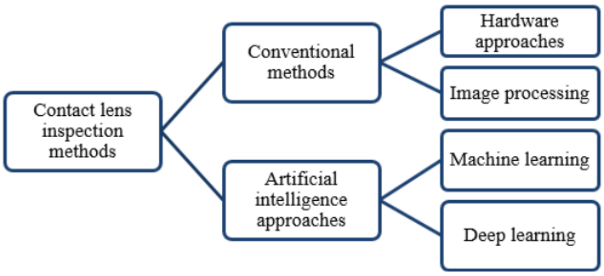

Figure 3. Summary of the division of contact lens inspection methods

3.1. Conventional methods

3.1.1. Hardware-based approach

An automatic optical inspection (AOI) system for contact lens defect inspection was developed by Chang *et al.* [16], which featured a suitable light source, camera, and image processing algorithms. Missing lenses and contact lens surface flaws are the most common defects. A lighting system with a fixed focus lens and a charge-coupled device (CCD) was used to collect contact lens images. An algorithm was utilized to check for defects after images have been collected. The designed algorithm can detect five different types of defects. The AOI system for contact lens inspection has been implemented as a prototype. Experiments have shown that the proposed system is reliable for in-line inspection. Coldrick *et al.* [17] compared the optimec JCF and the optimec is830 to a widely used optical coherence tomography (OCT) based geometric inspection instrument. Additionally, the optimec is830 examined several geometrical features of contact lenses only with a single tool. It was easier to measure geometric data, like sagittal depth and thickness, at the centre and edges of the lens, through OCT method. The optimec JCF is a common projection-based instrument, whereas the optimec is830 is an OCT-based instrument that used interferometry to generate an image of samples that are transparent or semi-transparent. Lee *et al.* [11] developed an OCT system with a frequency domain using optical fibers. Soft contact lens specimens were used to measure tomographic images of sample tissues. Tomographic images were measured using a magnifying projector and OCT for defective soft contact lenses, and an OCT system with a tunable wavelength of 1,200 nm to 1,400 nm was built. The defect could be confirmed on the 2D image of the magnifying projector, and soft contact lens defects could also be confirmed on the 2D OCT image in the sample where the shape of the edge defect can be confirmed with the naked eye, as shown in Figure 4.

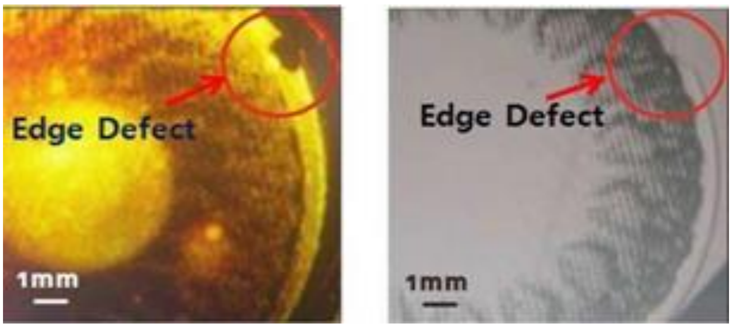

Figure 4. Edge defects of soft contact lens image resulted from OCT (left side) and resulted from contact lens analyzer (right side) [11]

Figure 5 shows another measurement of a microscopic bubble sample from a soft contact lens that was used for 3D stereoscopic image rendering using OCT. The tomography of the soft contact lens, which could not be seen with a magnifying projector, could be observed, and the shape of the bubble defect could be visualized more clearly, by interpreting and confirming the measured image in 3D.

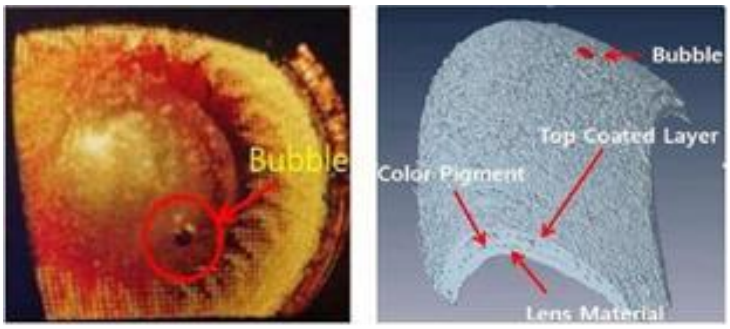

Figure 5. Bubble of soft contact lens image resulted from OCT (left side) and the result of 3D tomographic image (right side) [11]

When it comes to soft contact lens scratches, visual inspection with a magnifying projector made it difficult to determine whether the scratch is an internal or external defect. Considering this, being able to determine whether there are soft contact lens defects in the sagittal, coronal, and horizontal planes, which are tomographic planes along the direction, using the 3D rendering of OCT as shown in Figure 6 and Figure 7, is extremely valuable. A fairly dense tomography image must be taken to identify minute defects, which took a long time. Tomography imaging of soft contact lenses with OCT equipment is likely to be a useful method for finding defects such as edge defects, bubbles, and scratches [11].

A manual inspection tool was developed in 2016, to check the quality of transparent products with the brands ME5900 by microenterprise Inc. A fiber optic light source was used in this tool, which penetrated the workpiece before being projected onto the screen's surface. The researcher intended to build one by modifying semi-automatic inspection equipment and incorporating a rotary motor encoder based on the index system. This illustrated that the design increases the efficiency, productivity, and quality of soft contact lens inspection process. With the use of this indexer, 48 soft contact lenses were successfully inspected in one machine cycle, a performance that was previously only possible through human processes for the first soft contact lens inspection cycle, known as the optispec 1 cycle [18].

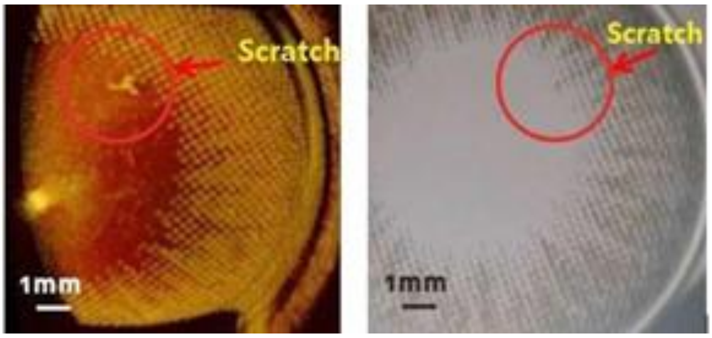

Figure 6. Scratch of soft contact lens image resulted from OCT (left side) and contact lens analyzer and (right side) [11]

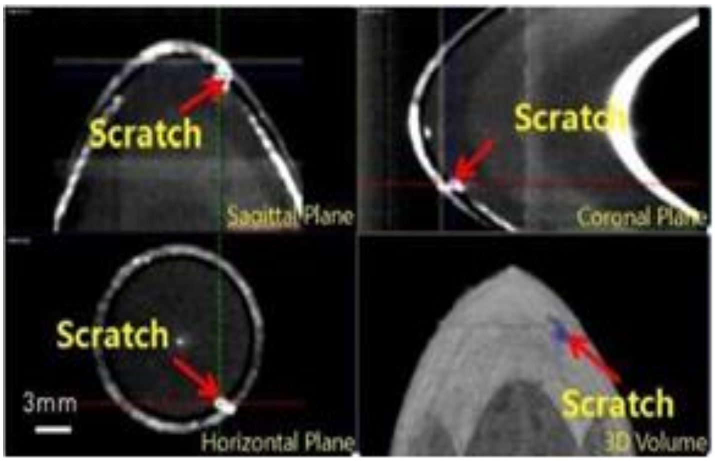

Figure 7. Scratch of soft contact lens image resulted from a 3D tomographic image [11]

3.1.2. Image processing approach

Image processing-based inspection methods were mostly picked by previous studies because it produced clear and precise results in contact lens detection. Image processing has advanced tools in the visual inspection over time. A low-pass filter and total variation were used as denoising techniques in 2010, to precisely localize the iris region's inner and outer boundaries and then locate those regions. To make the computation easier, iris images were standardized into the same size of 400×400 pixels. Then, local binary patterns (LBP) [19], [20] were employed to represent textural patterns in iris images. The LBP has shown to be a valuable texture descriptor, and texture analysis frequently employs it. The weighted LBP demonstrates its advantages when dealing with mixed databases, as well as its robustness in cross-camera experiments, indicating that texture primitives have a strong learning ability [21].

Doyle *et al.* [22] used the modified LBP to segment pupil, iris, and sclera regions. The image was not decomposed into blocks and each block is independently analyzed to create a large feature vector in this modified method. The extracted region is instead treated as a single large block. Next, Erdogan and Ross [23] located candidate points corresponding to the lens perimeter by traversing a small annular region near the segmented iris' outer boundary and locating candidate points. Then, these candidate points within the annular region were determined by looking at intensity distributions in the radial direction. Before running the stereo routines, contact lens-based iris images were scaled into 1,072×712 using imagemagick's convert function [24]. Following that, iris segmentation, estimation of three-dimensional (3D) points, and finally outlier removal and coarse segmentation were performed. An effective edge defect detection approach built on the local threshold method was proposed by Chang *et al.* [16]. They used Otsu's binarization threshold method, which can be modified to adjust for different lighting and lens settings as well as variations in grayscale based on by changes in the optical zone and edge region. Next, Gragnaniello *et al.* [25] used a real segmentation algorithm that neglects the eyelids and excludes normalization, as well as data from the iris and a part of the sclera. They extracted discriminative features using a rotation and scale-invariant descriptor (SID) and carried out the classification using the bag of words (BoW) method. Raghavendra and Busch [26] used OSIRIS V4.1 to perform iris segmentation and normalization. The OSIRIS V4.1 performed iris segmentation by using the viterbi search algorithm to detect the optimal path of the contours. The segmented iris is then normalized using OSIRIS V4.1's Daugman's rubber sheet expansion technique. In 2016, a soft contact lens detection (SCLD) algorithm was developed based on the multi-scale line tracking (MSLT) algorithm [27], for segmenting retinal vessels. This algorithm can extract soft contact lens boundaries and detect very faint edges. To detect occlusion from the contact lens area, a canny edge detector with a high threshold was used [28]. Iris segmentation without normalization was proposed by Gragnaniello *et al.* [29]. Canny edge detector used before applying the circular hough transform (CHT) to locate iris boundaries and generate 3D points. The image was processed with a large window median filter, which smoothed out the iris pattern while preserving the strong iris-sclera and iris-pupil edges, preventing the detection of useless edges in the region of interest (ROI).

Mandalapu *et al.* [30] employed image quality features computed with the blind/referenceless image spatial quality evaluator (BRISQUE) and texture features computed with binarized statistical image features (BSIF) to detect presentation attacks based on contact lenses. A classification method to identify the presence of soft lens in iris images was proposed in [31], and this work began with segmenting the lens boundary on top of the sclera region. The segmented boundary used as a feature, and local descriptors are used to extract it. To deal with the inhomogeneous shape and rotation of the lens boundary, the researchers used scale invariant feature transform to describe the original sclera region. The gradient orientation of the boundary was extracted using a gradient histogram. On the other hand, previous study [32] presented a new transparent contact lens detection method for classifying an eye image into no lens or transparent lens categories. In order to extract significant edge points in the sclera ROI, the input image was first segmented. To extract both ROIs that lie between two eyelids, scleral ROI segmentation was applied. Then, hough transform was used to localize the iris, dilate the edge output, and extract edge points at this stage.

Iris segmentation and Sobel detection were applied to detect the eyelids in search regions. To detect the edges, canny edge detection method was used [33]. Following the detection of edges, image smoothing techniques such as gaussian blurring and median blurring [34] were used to remove high-frequency noise and edges from the image, resulting in edges [35]. On the other hand, normalization was performed on iris images of 120×160 pixels and then used them as input. The DensePAD architecture was trained to encode discriminatory features for the binary classification task of actual against attack iris images using labelled iris images of both the real and attack classes. During the testing phase, the input iris images were normalized and passed through each dense block of the trained DensePAD network [36]. Zin *et al.* [37] proposed three image enhancement techniques which are histogram equalization (HE) [38], [39], contrast limited adaptive histogram equalization (CLAHE) [40]–[43], and homomorphic filter (HF) [42], [43]. These methods have been evaluated to give an even distribution of intensities throughout the image and improve the contrast of the soft lens boundary. They then performed normalization, segmentation, and removal of the eyelashes in the sclera region. In addition, summed-histogram method has been implemented as a solution to automatically classify the visibility status of the soft lens boundary. Image processing methods continue to produce good results year after year, but to improve industrial performance, inspection systems must be upgraded better than before and incorporate as many advanced tools as possible to achieve an accurate detection system and reduce processing time in the production line.

3.2. Artificial intelligence approaches
3.2.1. Machine learning approach

For classification, Zhang *et al.* [21] used the support vector machines (SVM) with the RBF kernel function. Because it avoids over-learning or over-fitting, SVM is a good choice for testing the feature extraction method. The SVM classifier is used to detect fake iris. Naive bayes, logistic, multi-layer perceptron (MLP), KStar, IBk, bagging, logit boost, JRip, ZeroR, OneR, NNge, J48, random tree, and random forest were applied in the automated classification of contact lens type in iris images. Over 96.5% of the images correctly identified as textured contact lenses [44]. After two years, they created robust classifiers for the detection of textured contact lenses, including nave bayes, logistic, multilayer perceptron, simple logistic, equential minimal optimization (SMO), and logistic model tree (LMT) [45].

CASIA and UNINA algorithms were applied in [46] to provide more insight into techniques for combating presentation attacks. The CASIA method feeds the iris image into SpoofNet-1, which determines whether or not it is a printed iris. In order to determine if the sample is a live iris or a contact lens, the iris was localized, and then normalized iris images were classified by the SpoofNet-2 network. GoogLeNet contributed as the basis for the development of SpoofNets. Next, Madhe and Holambe [47] used a novel convex optimization-based filter bank method to create a contact lens detection system. They used SVM classifier to categorize lenses into three categories: no lens (N), soft lens (S), and texture lens (T). The proposed method reported the highest accuracy of 99.5%. A lens quality-checking system based on machine learning was designed Natsupakpong and Nithisopa [15]. Machine learning classifiers such as naive bayes, bagging, logistic boost, JRip, J48, and random forest were used to assess the performance of lens inspection. With image pre-processing and data augmentation to extract features and improve the variation of the input image, machine learning has a 97% accuracy in the training model. The proposed method attained an overall average accuracy of 97.75% when 1,200 images were tested on the production line.

3.2.2. Deep learning and transfer learning approach

The previous study, which began in 2015, used images with soft contact lenses, contact lenses with textures or colors, and also no contact lenses to solve a three-class detection problem. In order to create a deep image representation, a convolutional network was used. An additional fully connected single layer with Softmax regression was also used for classification. Experiments have been done on two public iris image databases for contact lens detection, including the 2013 notre dame and IIIT-Delhi databases, as compared to a state-of-the-art (SOTA) approach. The results on the former database can reach a 30% performance increase over SOTA (from 80% to 86%) and comparable results on the final. These were very encouraging results because IIIT-Delhi database did not supply segmented iris images and, unlike SOTA, their approach did not yet segment the iris [48]. Multi-patch convolution neural network (MCNN) was introduced, He *et al.* [49], which can handle various types of fake iris images. It was recommended that CNN's input to be a multi-patch normalized ROI representation. Iris liveness detection has much higher accuracy than other state-of-the-art algorithms, according to experimental results. The proposed MCNN achieved the best results with nearly 100% accuracy. This proved that MCNN outperformed in contact lens iris detection. Raghavendra *et al.* [50] introduced ContlensNet for detecting contact lenses, which built through CNN architecture with fifteen layers that are configured for a three-class detection problem involving images with textured (or colored) contact lenses, soft (or transparent) contact lenses, and no contact lenses. The overfitting issue is resolved using the dropout regularization method, and ContlensNet was trained using a large number of iris image patches.

Gautam and Mukhopadhyay [10] introduced a transfer learning technique that extracts features using a pre-trained deep CNN, followed by PCA-based feature selection. Finally, a cubic support vector machine (cSVM) was utilized to train error-correcting output code (ECOC) multi-class models to detect the presence and type of contact lenses. The pre-learned CNN architecture was trained on a large dataset and now can be used to detect contact lenses on a smaller dataset. Singh *et al.* [51], a generalized hierarchically tuned contact lens detection network (GHCLNet) was implemented for detecting contact lenses, and they applied on three-class oculus classification, namely no lens, soft lens, and cosmetic lens. GHCLNet was developed based on the ResNet-50. One of the benefits of this network is that it operates on raw input iris images without the requirement for segmentation or pre-processing. Poster *et al.* [52] proposed a CNN-based architecture in their work on textured contact lens detection. In their suggested model, six MLPs (corresponding to the six features: BSIF, LBP, cooccurrenceof adjacent-LBP (CoA-LBP), histogram of gradients (HoG), DAISY, and scale-invariant descriptors (SID)) and one CNN are used (the 8-layer visual geometry group (VGG -based network). 8-layer CNN is referred to as the abbreviation of VGG-8. The robust and general low-level feature extractors from VGG-16 help in faster, more robust training, enabling to create a deeper and more discriminative CNN when compared to a randomly initialized version of the same network. On the other hand, Chen and Ross [53] presented a multi-task CNN learning strategy that can carry out presentation attack detection (PAD) and iris localization simultaneously. This method was developed using the CNN and VGG-Net frameworks. The

DarkNet-19 model was also used, which has previously been trained on the ImageNet 1000-class dataset with a 76.4% rank-1 accuracy, due to faster network communication and its improved model accuracy.

DensePAD, a novel iris presentation assault detection technique based on DenseNet was introduced by Yadav *et al.* [36]. According to an in-depth experimental evaluation, their technique surpasses the competition in recognizing iris presentation attack images across multiple databases. The DensePAD technique was also put to the test in real-world open-set iris presentation attack scenarios, demonstrating how challenging it is to discover iris presentation attack images from an unseen distribution. Next in 2020, an efficient and reliable iris presentation attack (PA) detector built on the DenseNet convolutional neural network architecture was introduced and developed using three distinct models which were fine-tuned, scratch, and pre-trained. On the proprietary dataset, the proposed method achieved a true detection rate of 98.58% with a false detection rate of 0.2%, outperforming state-of-the-art methods on the LivDet-2017 dataset [54].

MVANet [55], a generic deep learning-based presentation attack detection (PAD) network with several representation layers, was implemented and then compared to pre-trained models that have been trained using the ImageNet dataset including VGG16, ResNet18, and DenseNet. The average execution time for the MVANet was 6 minutes and 47 seconds per epoch. DenseNet took 7 minutes and 52 seconds per epoch, compared to 7 minutes and 41 seconds for VGG16. MVANet can be tuned more quickly than the baseline networks. When compared to other algorithms, the proposed MVANet had the highest accuracy of 95.11%.

4. SUMMARY OF PAST STUDIES

Most prior studies used different approaches in inspecting contact lens defects. Even though the hardware-based approach is the common approach implemented in the inspection sector, machine learning-based approaches still lead over the year. Table 1 in appendix summarizes the previous relevant works related to contact lens inspection methods including image processing, hardware-based, machine learning and deep learning, also classification methods within the accuracy.

Image processing is the most essential step in object detection. However, some previous researchers [10], [47], [48], [51], [54], [55] found image processing can be skipped to achieve excellent accuracy of the detection system and also to reduce the computation time. Common processes that have been studied before such as image segmentation and normalization are required before undergoing the next step which is feature extraction and classification. Based on Table 1 in appendix, it can be judged that artificial intelligence approaches involving machine learning and deep learning have become the most picked by prior researchers in this inspection field over the year.

5. CONCLUSION

In conclusion, hardware-based approaches seem to be useful and powerful tools for detecting defects and also, transparent and textured contact lenses. The industrial production process of contact lenses probably needs to be constructed with advanced tools based on recent technologies so that they can help in the inspection system to achieve accurate results of the inspection and reduce processing time. On the other hand, from the literature, there are limited studies have been done on contact lens inspection. Thus, it is believed that further exploration and enhancement of the inspection system will provide a wide alternative way to detect optical defects that are found under contact lenses.

APPENDIX

Table 1. Summary of contact lens related inspection or detection methods

Authors	Methods (image processing, hardware based)	Artificial intelligence approaches	Evaluation methods	Results
Zhang *et al.* [21]	Iris segmentation, iris denoising: using low pass filter and total variation methods, iris normalization into the same size 400×400	SVM classifier	Comparison between weighted LBP and standard LBP	Correct classification rate over 99%
Doyle *et al.* [22]	3 regions segmentation (pupil, iris, and sclera)	Naive bayes, bagging, logistic boost, jrip, J48, and random forest	Confusion matrix	Dataset I: CCR:65%; Accuracy 83%. Dataset II: CCR:71%; Accuracy 96%.
Erdogan and Ross [23]	Image denoising/smoothing-using gaussian filter, Iris segmentation	-	Confusion matrix, ROC curve	(ICE 2005 database): 76%, (MBGC Iris database): 66.8%

Table 1. Summary of contact lens related inspection or detection methods (*Continued)*

Authors	Methods (image processing, hardware based)	Artificial intelligence approaches	Evaluation methods	Results
Hughes and Bowyer [24]	Image scaling (1072×712) using Imagemagick's, iris segmentation, estimation of 3D points, outlier removal and coarse segmentation, Outlier removal and coarse segmentation	-	RANSAC algorithm	-
Doyle *et al.* [44]	Iris, pupil, and sclera segmentation	Naive bayes, Logistic, MLP, KStar, IBk, Bagging, Logit boost, JRip, ZeroR, OneR, NNge, J48, random tree, random forest	Cross-fold evaluation	Accuracy over 96.5%
Gragnaniello *et al.* [25]	Iris segmentation using CHT canny edge detector	SVM classifier	Bag of words model	Highest accuracy: 93.17% (Notre-Dame-I database)
Chang *et al.* [16]	Otsu's binarization threshold method	-	-	The machine AOI method had accuracy reached 95.5%.
Raghavendra and Busch [26]	OSIRIS V4.1 method for iris segmentation and normalization	A linear SVM	Gabor transform and sparse representation classifier, 10-fold cross validation method	overall performance is 92.22% (VSIA database), small ACER of 0.29%
Doyle *et al.* [45]	Iris, pupil, and sclera segmentation	Naive bayes, logistic, multilayer perceptron, simple logistic, SMO, and LMT.	Confusion matrix	CCR on novel lenses is about to 86%
Silva *et al.* [48]	Image cropping (112×112 pixels), not performing image preprocessing and segmentation	CNN with additional fully-connected single layer with softmax regression	CLDnet (network for contact lens detection)	Accuracy: 80%-86%
Lovish *et al.* [56]	Fusion of LPQ and BGP texture description	SVM classifier	Evaluation based on CCR and false acceptance rate	CCR%: 98.91%
Gragnaniello *et al.* [29]	Iris segmentation without normalization	SVM classifier	Bag-of-Features (BoF) model, inspired by the Bag-of-Words used in text classification	Highest accuracy: 93.67% (Notre-Dame-I database)
He *et al.* [49]	Iris localization, segmentation, normalization	MCNN	Spoofnet, Weighted LBP, HVC+SPM are used for comparison	MCNN achieved the best results with nearly 100% accuracy on ND-Contact and CAISA-Iris-Fake datasets
Raghavendra *et al.* [50]	OSIRIS v4.1 method for iris segmentation and normalization, image resizing (32×32 pixel), iris image sampling	Deep CNN, Dropout technique to reduce overfitting	-	IIITD Database; CCR% = 94.65% ND database; 92.60%
Gautam *et al.* [10]	-	SVM classifier	cSVM	Accuracy 96.39%
Mandalapu *et al.* [30]	BRISQUE and texture features computed from BSIF	-	SRKDA, fischer discriminant ratio	-
Zin *et al.* [31]	Iris segmentation using CHT, iris normalization using Daugman's rubber sheet, summed histogram, ridge detection algorithm	a non-linear SVM with radius basis function kernel	Confusion matrix	Accuracy 90.69%
Kumar *et al.* [32]	Sclera ROI segmentation, Iris localization using hough transform, dilation of edge output, edge point extraction	SVM classifier	Kernel SVM classification	Highest accuracy of 90.63% for NotreDame I database
Yambay *et al.* [46]	Image scaling to the size of 224×224, image localization, and normalization	SpoofNet-1, SpoofNet-2 (architecture based on GoogLeNet)	-	-
Madhe *et al.* [47]	-	SVM classifier	-	CCR of intra camera: 96.8% and 99.5% (IIITD cogent and vista dataset), CCR of multicamera: 78.51%

Table 1. Summary of contact lens related inspection or detection methods *(Continued)*

Authors	Methods (image processing, hardware based)	Artificial intelligence approaches	Evaluation methods	Results
Singh *et al.* [51]	-	GHCLNet (inspired by the ResNet-50 model)	-	Accuracy: 95.57% (ND combined database) and 94.82% (IIITD combined database)
Poster *et al.* [52]	Image were resizing into 224×224-pixel size	Six MLPs (corresponding to the six features: BSIF, LBP, CoA-LBP, HoG, DAISY, and SID) and one CNN (8-layer VGG-based network)	Scikit-learn	-
Chen *et al.* [53]	Iris localization and presentation attack detection	CNN, VGGNet framework and Darknet-19 model	-	-
Yadav *et al.* [36]	Iris segmentation and normalization	DenseNet based CNN architecture	Structural and textural features (DESIST), multi-level haralick VGG fusion (MHVF) algorithm	Total error of the proposed DensePAD on the WVU UnMIPA database is 1.93%
Natsupakpong *et al.* [15]	Segmentation using canny filter, blurring image with gaussian filter, finding edge with laplace filter, segment and blur image using gaussian filter, erode image	CNN	-	Performance accuracy was 97.75%
Sharma *et al.* [54]	-	D-NetPAD based on the DenseNet CNN architecture, three different models were created; pre-trained, scratch and fine-tuned D-NetPAD	Spatial frequency analysis	True detection rate was 98.58% and false detection rate was 0.2%
Zin *et al.* [37]	Image enhancement, sclera region segmentation and normalization, eyelash removal, summed histogram, ridge detection	SVM classifier	Summed histogram	Accuracy over 92%
Gupta *et al.* [55]	-	CNN framework: VGGNet, ResNet18, DenseNet, proposed MVANet	t-distributed stochastic neighbor embedding (t-SNE) visualization plots	Accuracy of proposed MVANet: 94.90% and 95.11% (Cogent and vista sensor images)
Agarwal *et al.* [57]	Image enhancement using CLAHE algorithm, HE and gamma correction	Shallow and deep CNN models	Compare to SVM, DenseNet, VGGNet, ResNet18, MVANet)	Accuracy of proposed algorithm was 97.12%, higher than other methods

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