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A Comprehensive Study on the Automatic Identification of Diabetic Retinopathy

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ABSTRACT

An eye condition known as diabetic retinopathy is caused by a higher blood sugar ratio. It usually doesn’t have any symptoms at the early stage, but in the later stage, the symptoms are visible, and the patient can find it difficult to see and can have irritation in the eye, which may result in blindness. Early discovery of it can lessen the spread of the disease in the eyes. Historically, diabetic retinopathy diagnosis was manual due to a lack of computerized technology. Manual detection-based methods have low accuracy, are time-consuming, and have side effects. Many methods have been put forward by researchers in order to discover diabetic retinopathy, such as machine learning, deep learning, image processing, data science, etc. These methods have used different datasets, including MESSIDOR, Kaggle, FUNDUS, EyePACS, DIRETDB1, macular optical coherence tomography, etc. In this paper, some of these recent proposed methods to detect diabetic retinopathy have been reviewed. The datasets that were employed by different techniques and the attained outcomes are presented in this paper. Also, the challenges and future plans of those methods are described. The comparative analysis of those methods will be helpful for a more thorough understanding of the detection of the disease.

Keywords: Diabetic Retinopathy; Retinal Images; Deep Learning; Machine Learning; Image Processing

INTRODUCTION

Retinopathy caused by diabetes, or DR, is among the main reasons behind sightlessness. DR damages the macular blood veins in a diabetic patient. Diabetic retinopathy falls into two distinct categories: proliferative DR and non-proliferative DR. "NPDR" refers to the initial phases of the illness and is broken down into three further groups: mild, moderate, and severe. One micro-aneurysm, a little red circular mark around the tip of blood vessels, is present in the mild stage. The moderate stage is characterized by a flame-shaped retinal hemorrhage caused by the MAs splitting into the deeper regions of the retina [1]. Figure 1 shows the condition of the eyes during different stages of diabetes Retinopathy.

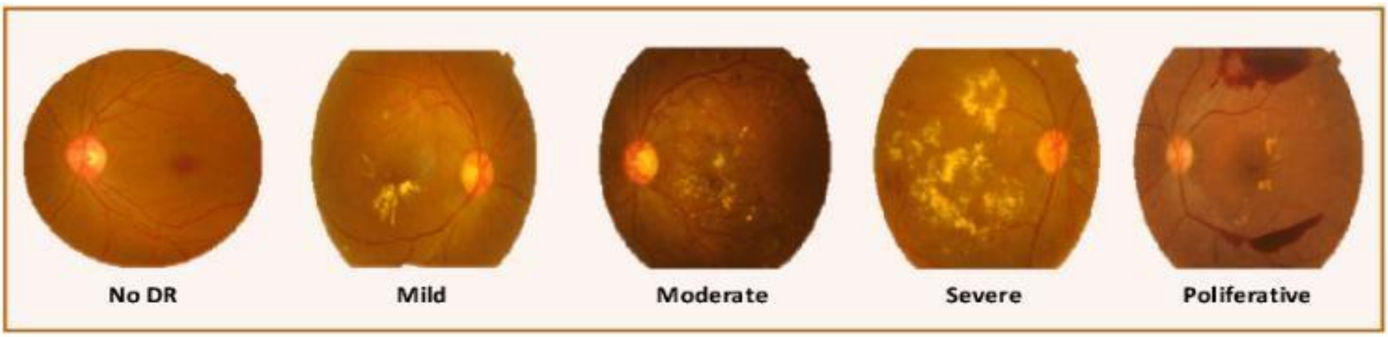

Fig. 1 The DR Stages: (A) Normal Retinal (B) Mild DR, (C) Moderate DR, (D) Severe DR, (E) Proliferative DR [2]

The primary cause of visual impairment among individuals in developed nations who are of working age is diabetic retinopathy. Diabetic retinopathy is the term used to refer to a condition where blood and fluids seep into the surrounding tissue. It happens because of the destruction of the blood veins inside the macula. This fluid leakage leads to wool-like patches (also called soft exudates), hemorrhages, microaneurysms, and hard exudates. Patients with diabetic retinopathy may not even be aware of their condition until the oddities of the retina have progressed to the point where medical care becomes difficult or even impossible [3].

According to the American Academy of Ophthalmology (AAO), approximately 34.6% of individuals with diabetes globally have DR. 10.2% (28 million) of people with diabetes have DR, which can be fatal to their eyesight. A thorough awareness of the risk factors, prompt therapeutic intervention, and early diagnosis are necessary for the effective management of DR. Effective intervention is critical to slowing the development of DR and, thus, lowering the chance of vision impairment. Finding people who are in danger of getting DR early on is the first step in this process. Additionally, each patient can receive the best care possible by being categorized based on their particular risk levels. However, most DR patients may not take medical assistance until the disease reaches the proliferative stage. It can cause permanent damage because there are no characteristic symptoms in the early stages of the illness [4].

In the past, experts used manual testing to diagnose diabetic retinopathy because there was no computerized technology available. It is difficult and prone to error for clinicians to manually diagnose this illness. As a result, a number of computer vision-based methods have been put forth for automatic identification of different phases of DR from retinal images. Nevertheless, these techniques can only classify the various stages of the disease with extremely poor precision, especially for the early phases, and lack the ability to accurately represent the underlying complex features [1]. It takes time to manually screen retinal photos to detect small lesions in the initial phase of DR, and it takes time to manually grade retinal images, which is error-prone and not patient-friendly [5] [6]. Numerous physical exams, including the test of clarity of vision, dilation of the pupil, and optical coherence tomography, can identify diabetic retinopathy, but they take time and have negative consequences on the patients [7]. Due to these factors, doctors are increasingly using techniques including image processing, machine learning, deep learning, and others to identify diseases. These techniques speed up the diagnosis process by giving physicians precise results in a short amount of time.

Research Problem

Irregular variations in blood sugar levels are experienced by diabetics, and these variations can result in hyperglycemia and harm too many organs, especially the eye. Type I diabetes is characterized by the body becoming insulin-dependent and necessitating insulin injections or treatment; Type II diabetes is characterized by the body producing adequate insulin but not utilizing it for energy conversion, resulting in abnormal blood sugar levels. Diabetic retinopathy is more prone to occur in patients as a result of these abnormalities, which impair eyesight by obstructing the blood vessels in the retina with photographic receptors. Variable vision, eye fatigue, hazy vision, abnormalities of the cornea, double vision, eye pain, and vision issues unrelated to presbyopia are among the symptoms. Angiogenesis is a diagnostic tool used to identify changes in diabetic blood vessels and retinal blood leaks that can lead to blindness and other severe visual impairments [8]. About 10% of diabetics may develop vision-threatening diabetic retinopathy (VTDR), which has early symptoms such as visual impairment, discomfort in the eyes or redness, and a sensation of moving forms in the visual field. Diabetes duration, uncontrolled diabetes, and hypertension are recognized indicators of risk for the development of diabetic retinopathy disease (DR) [9].

Several techniques were employed to identify DR. Prior to 2020, image processing, machine learning, and deep learning were utilized. In order to detect DR, these techniques have been upgraded and refined in recent years. Deep learning is the approach most frequently employed for this disease's identification among all the publications this article has studied.

LITERATURE REVIEW

Researchers employ a range of algorithms, methodologies, strategies, and procedures in their numerous investigations on the detection and prediction of diabetic retinopathy; these will all be considered as part of the theoretical framework for this investigation. In the process, it also makes it possible to build the framework for the research.

Ramasubramanian et al., [10] proposed an image-processing-based early detection approach in order to discover diabetic retinopathy. By making use of color fundus photos with non-dilated pupils as the dataset, it applied the K-Nearest Neighbors Classifier. 97% of the attempts were successful. Priya et al., [11] recommended applying machine learning methods like support vector machines, Bayesian classification, and probabilistic neural networks. A total of 350 fundus pictures were used, of which 100 were used for testing and 250 for training. The accuracy of PNN is 89.5 percent, that of the Bayes classifier is 94.4 percent, and that of SVM is 97.6 percent, according to the results. This suggests the SVM model outperforms all other models. The purpose of this investigation by Carrera et al., [3] is to help people discover diabetic retinopathy early on by proposing computer-aided detection that utilizes the digital processing of retinal pictures. On 400 retinal pictures classified using a 4-grade non-proliferative diabetic retinopathy scale, SVM was applied. The model's predictive ability was 94%, and its maximum sensitivity was 95%. Dutta et al., [12] proposed an automated knowledge model to identify DR causes using backpropagation, deep, and convolutional neural networks. FUNDUS retina images were used, with DNN outperforming BNN due to time efficiency and better training accuracy. Poor CNN training results in higher error rates. Chetoui et al., [13] explored the application of many textures attributes for deep reinforcement learning (DR), primarily local energy-based shape histograms (LESH) and local ternary patterns (LTP). The 1200 photos in the MESSIDOR dataset are used to evaluate how well the recommended methods work. According to the experimental data, the most successful approach is LESH, which applies SVM using the radial basis function (SVM RBF) to achieve a precision of 0.904. Similarly, the ROC curve research shows that LESH with SVM-RBF performs best in terms of AUC (area under curve), coming in at 0.931.

Gao et al., [14] created a collection of DR fundus photos annotated with the suitable treatment technique that is needed in order to computerize the detection of DR and offer DR patients proper advice. Here, DR fundus image datasets are utilized to assess deep convolutional neural network models. In the studies, it was able to attain a success rate of 88.72% for a four-degree classification challenge. Zhang et al., [15] proposed Deep DR, an automated DR detection and grading method. Convolutional neural networks (CNNs), ensemble learning, transfer learning, and modified standard deep neural networks were employed. Clinical ophthalmologists assess it using a superior dataset of DR medical pictures before labeling it. With 97.5% sensitivity and 97.7% specificity, and 97.7% area under the curve, the identification model outperforms the others, according to the results. In the meantime, the grading model attains 98.1% sensitivity and 98.9% specificity. Li et al., [16] evaluated the most advanced deep learning models to detect DR lesion, DR lesion segmentation, and DR classification. Using 9598 patients' 13,673 fundus photos, scientists assessed the performance of cutting-edge deep learning algorithms for object identification, semantic segmentation, and image classification. It received a DR classification accuracy of 0.8284. The primary goal of the method proposed by Naveen et al., [17] is to use image processing techniques to detect the eye illness known as diabetic retinopathy (DR). Using an eye-retinal fundus picture, it is evaluated. It has obtained a 98% accuracy rate. Qummar et al., [1] suggested that in order to detect diabetic retinopathy, the paper proposes a deep learning ensemble approach. A group of five deep convolution neural network (CNN) models (Resnet50, Inceptionv3, Xception, Dense121, and Dense169) were trained using the publicly available Kaggle dataset of retinal photos in order to enhance the categorization for various phases of DR. It used the same Kaggle dataset. The experimental outcomes show that, unlike current methods, the suggested model identifies every stage of DR and outperforms them.

This work by Samanta et al., [18] employed color fundus photography and CNN's transfer learning-based architecture to automate the diagnosis of diabetic retinopathy. A dataset with skewed classes, consisting of 419 validation photos and 3050 training images, is used for the process. It achieved an 84.10% validation accuracy. On the training data, the Kappa score is 0.9809, while on the validation data, it is 0.8836. Alfian et al., [19] proposed an early indication of diabetic retinopathy (DR) according to specific risk variables. This study suggests combining a deep neural network (DNN) with recursive feature elimination (RFE). For the suggested and several state-of-the-art models, early stages of DR were predicted using a publicly accessible database of 133 diabetic patients. With 82.033% prediction accuracy, the suggested model was successful. Abdelsalam et al., [20] has developed a novel multifractal geometry-based method for DR early detection. The Support Vector Machine (SVM) technique, which is part of a supervised machine learning approach, was assessed on macular optical coherence tomography angiography (OCTA) pictures and demonstrated 98.5% accuracy. Erciyas et al., [21] proposed an approach by utilizing deep learning for automatically identifying and categorizing lesions associated with diabetic retinopathy, regardless of datasets. It made use of transfer learning, attention mechanisms, faster RCNNs, and deep learning-based techniques. Using the Kaggle and MESSIDOR datasets, the approach was tested and yielded results of 99.1% and 100% ACC and 99.9% and 100% AUC, respectively. Reguant et al., [22] suggested to identify the intrinsic picture characteristics that are used in CNN's decision-making process. This paper initially employs a CNN visualization technique. Next, it examines those characteristics. The studies are conducted using publicly accessible fundus data sets (EyePACS and DIARETDB1), and the results show an accuracy of 89 ~ 95% with an AUC, sensitivity, and specificity of 95 ~ 98%, 74 ~ 86%, and 93 ~ 97%, respectively.

Deepa et al., [5] presented a group of models for deep convolutional neural networks (CNNs). It provides 96.2% accuracy in classification with fivefold cross-validation when used to accurately diagnose and grade diabetes mellitus using fundus images. Zhao et al., [4] proposed that researchers create models that predict diabetes-related retinopathy risk. 5 machine learning techniques are used: K-Nearest Neighbor (K-NN), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and Extreme Gradient Boosting (XGBoost). It used data of 7943 patients, and out of the five models, the XGBoost model demonstrated the greatest ability for prediction, with an AUC, accuracy, sensitivity, and specificity of 0.803, 88.9%, 74.0%, and 81.1% respectively. The purpose of the study that was conducted by Sumathy et al., [23] is to use patient data to detect diabetic retinopathy early. On a dataset comprising 900 diabetic patients, it applies logistic regression, KNN, SVM, bagged tree, and boosted tree classifiers. With 10% hold-out validation, the boosted tree yielded the highest level of accuracy in classification (90.1%). Moreover, KNN attained 88.9% accuracy. Skouta et al., [24] suggested altering the CNN UNet's architecture for the purpose of detecting hemorrhaging of the retina in fundus pictures. The DIARETDB1 and IDRiD datasets are used to evaluate it. The trained neural network then showed a substantial improvement, successfully segmenting the bleeding and achieving 80.49%, 99.68%, and 98.68%, respectively, for sensitivity, specificity, and accuracy. Mohanty et al., [6] suggest two deep learning (DL) models for DR diagnosis and categorization: the DenseNet 121 network and a hybrid network that combines the VGG16 and XGBoost classifiers. The authors previously processed a set of retinal pictures from the APTOS 2019 Blindness Detection Kaggle Dataset in order to assess the two DL models. According to the findings, the DenseNet 121 model had 97.30% accuracy, whereas the hybrid network had 79.50% accuracy.

Swapna et al., [25] proposed system uses deep learning for the discovery of diabetic retinopathy in macular fundus images. It makes utilization of data augmentation to balance data and divide pictures into normal as well as abnormal categories. The VGG16 CNN architecture model outperforms the Densenet121 model with an accuracy of 94.57%. Palaniswamy et al., [26] used retinal fundus images to introduce an IoT and deep learning-facilitated diabetic retinopathy detection model (IoTDL-DRD). Making use of a cloud server, the method gathers data from Internet of Things devices and processes it. For an efficient diagnosis, the model makes use of MFORG segmentation, a dense network feature extractor, and a long short-term memory classifier. According to a comparison study, the method is better.

Overview of Datasets

FUNDUS: The Joint Shantou International Eye Centre (JSIEC), located in Shantou city, Guangdong province, China, is the source of all 1000 fundus photographs, which are divided into 39 classes. These pictures make up a very minor portion of the 209,494 fundus photos that will be included in our deep learning platform's training, validation, and testing. Of the 1000 photos, 997 have .jpg extension, while 3 have .tif extension. This dataset is used in [17] where the methods by which the DR is not discovered in the healthy fundus picture and the afflicted DR is found in the fundus pictures are involved in this method. 350 fundus photos in total were used in [11], of which 250 were utilized for testing and 100 for training. This paper [12] uses 2000 FUNDUS photos with diabetic retinopathy as a data set, consisting of 35,000 training and 15,000 testing images, with a 7:3 training-to-testing ratio. Fivefold cross-validation is utilized for training and testing on a dataset of 2290 fundus pictures in this paper [5]. This paper [27] used digital fundus color images with 256 gray levels for each individual red, green, and blue pixel component, acquired at a resolution of 1150 × 1234 from the fundus camera. 415 fundus photos of diabetic retinopathy make up the data for this paper [25]. From 2016 to 2018, 13,673 color fundus photos from 147 hospitals encompassing 23 Chinese counties—84 of which are classified as grade-A major institutions—were gathered by the authors of this study [16]. The 9598 patients who contributed these pictures ranged in age from 1 to 100.

MESSIDOR: The MESSIDOR database, which comprises 1200 color and quantitative images of the ocular fundus of the posterior pole taken with a 45-degree viewing angle by three ophthalmologic departments, was used in this study [3]. Eight bits color plane was employed for capturing the photos at 1440 x 960, 2240 x 1488, or 2304 x 1536 pixels. Four hundred pictures were taken without pupil dilation and eight hundred with pupil dilation (a single drop of Tropicamide is at 0.5%). The authors [7] used 1200 losslessly compressed photos with 450 FOV at various resolutions from the publicly accessible MESSIDOR collection. Every image has a grading grade that ranges from R0 to R3.This dataset is used in [21], [28], [14]. In this work [26], the MESSIDOR dataset is used to validate the IoTDL-DRD method's performance. 1744 fundus photos are included, categorized into five class designations. Using the 1200-picture MESSIDOR dataset, the paper's [13] suggested strategies are assessed for performance.

APTOS 2019 Blindness Detection: This is from kaggle.com. It has 5593 files. Among which 5590 are in .png form and 3 are in .csv form. The APTOS dataset was utilized for both training and testing of the models in [6] with 80% of the data utilized for training and 20% for testing. Over 50 epochs, the training procedure was carried out.

Kaggle DR: The Kaggle Dataset contains 80,000 photos in total, of which 100 are used for training the detection stage, 4900 are used for testing the detection stage, 3920 are used for training the classification stage, and 980 are used for testing the classification stage. The paper [1] used Kaggle dataset by modifying it, which comprises 35126 color fundus pictures with a resolution of 3888 × 2951. The study [21] used

980 data and 3920 data for testing and training, respectively, from the Kaggle dataset. Of the 3920 training data, 784 were utilized for validation. The paper [29] makes use of the Kaggle database. Using a scale of 0 to 4, the doctors assessed every photograph to check whether DR was present or not in accordance with ETDRS standards.

EyePACS: The paper [22] rated 35,126 fundus images from EyePACS into five distinct categories: no DR, mild NPDR, moderate NPDR, severe NPDR, and proliferative DR, using an e-grading system. The majority had no DR, resulting in imbalanced data. The study [28] used EyePACS, containing 88,702 color retinal fundus photos from 44,351 patients, to train on 35,126 marked images and test on 53,576 pictures from 26,788 patients.

RESULTS ANALYSIS

A comparison of the datasets utilized in the various studies conducted to detect diabetic retinopathy is shown in Table 1.

Table 1: A Survey Of Current Research On Diabetic Retinopathy Identification

Dataset	Paper	Method	Result
	[5]	Multistage Patch-based Deep CNN (MPDCNN)	Accuracy:96.2%
		-(InceptionV3, Xception) + Artificial Neural Network (ANN) +SVM	
FUNDUS	[11]	Probabilistic Neural Network (PNN)	Accuracy:89.6%,
		Bayesian Classification	Accuracy:94.4%
		Support Vector Machine (SVM)	Accuracy97.6%
	[12]	Back Propagation NN	Accuracy:62.7%
		Deep Neural Network (DNN)	Accuracy:89.6%

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		Convolutional Neural Network (CNN)	Accuracy:76.4%
	[17]	Contrast Limited Adaptive Histogram Equalization (CLAHE)	Accuracy:98%
	[3]	Support Vector Machine (SVM)	Accuracy:85.00%
	[21]	Faster RCNN+ Attention Mechanism.	Accuracy:100%
MESSIDOR	[25]	VGG16	Accuracy:94.57%
		DenseNet121	Accuracy:79.75%
	[26]	Internet of Things Deep Learning – Diabetic Retinopathy Diagnosis (IoTDL-DRD)	Accuracy:99.08%
		-Mayfly optimization based region growing (MFORG) + DenseNet + Long	
		Short Term Memory (LSTM) + Honey Bee Optimization (HBO)	
	[28]	ResNetGB	Accuracy: 98.88%
	[1]	ENSEMBLE MODEL	Accuracy:80.08%
		-Resnet50 + Inceptionv3 + Xception,+ Dense121 + Dense169	
Kaggle	[6]	Hybrid Network combining VGG16 and XGBoost Classifier	Accuracy:79.50%
		DenseNet 121 network	Accuracy:97.30%.
	[21]	Faster RCNN+ Attention Mechanism.	Accuracy :99.1%
	[29]	AI-based Smart Teleopthalmology Application (Android application)	Precision:91.44%
			Sensitivity:92.51%
			Specificity:91.35%
DIARETDB1	[24]	Modifed CNN UNet architecture	Accuracy:98.68%
EyePACS	[28]	ResNetGB	Accuracy: 99.73%
EyePACS+ DIARETDB1	[22]	Inception	Accuracy:94.00%
		Resnet 50	Accuracy:89.00%
		Inception resnet	Accuracy:94.00%
		Xception	Accuracy:95.00%
Fundus Images Dataset-2 (4476 images)	[14]	Deep Convolutional Neural Network (DCNN)	Accuracy:88.72%
Fundus Images Dataset-3 (3469 images)	[18]	DenseNet	Accuracy:84.10%
OCTA images	[20]	SVM	Accuracy:98.5%
Fundus Images Dataset-4 (7943 diabetic patients)	[4]	Random Forest (RF)	Accuracy:76.40%
		Logistic Regression (LR)	Accuracy:79.90%
		Support Vector Machine (SVM)	Accuracy:73.10%
		K-Nearest Neighbor (K-NN)	Accuracy:74.20%

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		Extreme Gradient Boosting (XGBoost)	Accuracy:53.70%
NHISS Korea dataset (133 diabetic patients)	[19]	Recursive Feature Elimination RFE) + Deep Neural Network (DNN)	Accuracy: 82.03%
900 diabetes patients	[23]	Logistic regression	Accuracy:82.10%
		KNN	Accuracy:85.80%
		SVM	Accuracy:82.70%
		Bagged tree	Accuracy:79.00%
		Boosted tree classifiers	Accuracy:86.60%

Challenges and Future Scopes

A review of various techniques for identifying diabetic retinopathy is included in this publication. The papers evaluated various approaches while addressing certain difficulties. For example, the primary issue, as the

research [3] reviewed, is that certain retinal scans do not show microaneurysms. The primary difficulty with the research [12] is determining each feature class threshold with accuracy. The suggested algorithm's difficulty, according to the paper [5], is to further classify PDR photos according to high-risk attributes. The quality of processed images, ranging from 35% to 65%, poses challenges for doctors in diagnosing OCTA images and identifying lesions in fundus pictures, necessitating the development of advanced algorithms [20] [16].

To further increase the accuracy of the initial stages in the future, authors [1] want to train particular models for particular phases and then combine the results. The findings [3] are promising, and the provided algorithms will be included in a method for screening diabetic retinopathy in a subsequent scientific study. Future research will explore soft and hard exudates, texture analysis to improve retinopathy detector precision and sensitivity, with updates incorporating more equipment data and a comprehensive pilot study. The display of features acquired by CNNs is significant because it may increase the efficiency of diagnosis by determining the source areas of characteristics connected with a particular categorization outcome. Additionally, using the results of the visualization, clinicians may accurately diagnose patients. It is vital to have a theoretical discussion on the creation and analysis of ensemble frameworks when dealing with medical datasets of limited size [15] [14] . The employed dataset will be expanded and further enriched by the authors [16] , taking into account new disease kinds and the population.

CONCLUSION

This article carried out a comprehensive review of automated DR detection methods from research articles, highlighting their shortcomings and outcomes in identifying the disease when methods were applied to fundus images, the DIARETDB1, MESSIDOR, and Kaggle datasets, along with data gathered from DR patients. The disease was first explained, along with the drawbacks of utilizing manual methods to detect DR. Following that, computerized approaches—which include the names of the methods, the datasets used, and the results obtained—were thoroughly reviewed and employed in several research articles. The datasets utilized in multiple research projects were then detailed, and based on the identical datasets applied in other papers, a comparative analysis was given. In the end, the primary obstacles facing automated DR methods of detection were depicted, including their potential future applications. Future research should assess these techniques on significantly larger high-resolution image datasets for diagnosing diabetic retinopathy in order to generate highly reliable, quick, and real-time diagnosis settings.

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