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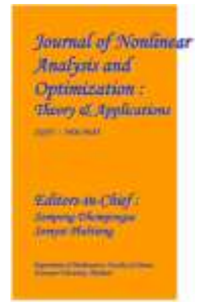

A REVIEW OF DEEP LEARNING-BASED SMART IOT HEALTH SYSTEM FOR BLINDNESS DETECTION USING RETINAL IMAGES

[1]**Deekshitha Dabbeeru,** [2] **Dodla Kavya Sri** UG Students, Department of ECE, GMR Institute of Technology, Rajam, Andhra Pradesh, India
[3] **Yogesh Misra**, Professor, Department of ECE, GMR Institute of Technology Rajam, Andhra Pradesh,
Corresponding author: yogesh.m@gmrit.edu.in

Abstract— This paper Review the Deep Learning-Based Smart IOT Health System For Blindness Detection Using Retinal Images. The increasing concern of diabetic eye disease, a leading cause of blindness particularly in populous Asian countries like India and China. The goal is to employ deep learning techniques, specifically a fine-tuned EfficientNet-B5 model for automating the detection of blind spots in retinal images. The proposed model outperforms CNN and ResNet50, offering a promising solution for efficient and accurate blindness identification in diabetic patients. The GCA-EfficientNet (GENet) model, incorporating adaptive convolutional kernel sizes, is proposed for DR severity diagnosis in color medical images. Transfer learning and a cosine annealing learning rate strategy are employed in training. This model achieves high accuracy, precision, sensitivity, and specificity. A deep learning smart health-based system is designed to detect DR which is a leading cause of blindness. DR poses a serious threat to vision and can be cured using retinal images and an IOT framework. Deep Learning-based Smart Healthcare is gaining much attention because it can be used in real-time situations affecting everyone's lives. This interest has increased even more with the combination of IOT. One major cause of blindness in working-age people is diabetic eye disease. This has made it difficult for doctors to screen and diagnose all these patients. Diabetic Retinopathy is a major cause of blindness which can cause even permanent blindness if not diagnosed and treated promptly. The successful development of a functional prototype for a smart shoe insole capable of monitoring arterial oxygen saturation (SpO2) levels in the feet of diabetic patients using photoplethysmography (PPG) signals. The continuous assessment of SpO2 levels in diabetic foot ulcer (DFU) patients is crucial for understanding ulcer severity, monitoring wound healing, and alerting clinicians to critical limb ischemia. The wearable insole integrates seamlessly with the Internet of Things (IoT) through a custom Android mobile application, facilitating "at-home" monitoring. The study involved testing on 20 healthy subjects, demonstrating the insole oximeter's ability to estimate SpO2 levels at the toe with an average error of approximately 2.6% compared to a reference oximeter on the finger. Validation using the perfusion index (PI) indicated acceptable blood flow in both monitoring sites. Results showed that alternating current components of PPG signals significantly contributed to SpO2 estimations, and a K-nearest neighbor (KNN) classifier achieved a high accuracy of 96.86% in predicting monitoring sites (finger or toe).

Keywords— DR, IOT, CNN, GCA Efficient, PPG, DFU.

I. INTRODUCTION & REVIEW

There has been increasing attention to the convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) for the development of efficient smart healthcare systems. This convergence is enabling more effective detection of various health diseases. Diabetes, a prevalent chronic disease worldwide results from the body's inability to produce or use insulin effectively causing high glucose levels in the blood. The World Health Organization (WHO) reported over 1.6 million deaths due to diabetes in 2016. Diabetic patients are at risk of complications such as heart stroke, kidney failure, and Diabetic Retinopathy (DR), a severe condition that can lead to complete blindness. Approximately 25% of diabetic patients worldwide are affected by DR, making it a complex disease. Long-term diabetes can progress to DR causing partial or permanent vision impairment particularly affecting the working-age population, a crucial demographic for any growing economy. India alone has a significant and rapidly growing diabetic population. Detecting DR in its early stages is challenging but crucial. Initial symptoms are subtle, often leading to irreversible damage before diagnosis through medical tests. Efficient and trained professionals can manually evaluate digital color fundus photographs of the retina to detect DR but this process is time-consuming and demands highly skilled medical practitioners. Deep learning, a popular approach in healthcare and patient monitoring particularly in medical image processing, is employed in this study. Convolutional Neural Networks (Conv-Nets), a deep learning approach effective for image analysis are utilized with a focus on the Efficient-Net architecture for analyzing retina images and detecting DR symptoms [1]. Diabetic retinopathy (DR), a major complication of diabetes results from retinal damage due to elevated sugar levels. With the global diabetic population projected to exceed 700 million by 2045, DR cases are expected to reach 191 million by 2030. Timely examination and treatment are crucial for preserving visual acuity. Common diagnostic methods include 2D color fundus images and 3D optical coherence tomography (OCT). Deep learning in image processing, particularly using color fundus images offers an efficient and cost-effective means for DR severity diagnosis. Global Channel Attention (GCA) mechanism in the DR severity classification model, GCA-EfficientNet (GENet), which fully considers feature map correlations. Key contributions include proposing GCA to update attention weights during model training, introducing an adaptive one-dimensional convolution kernel size calculation, and combining GCA with EfficientNet. The GENet model, trained through transfer learning, achieves high accuracy (0.956), precision (0.956), sensitivity (0.956), and specificity (0.989) in DR severity classification [2]. To address the rising prevalence of diabetes and its associated complications, particularly in children, innovative solutions are being developed. One such advancement is a wearable shoe insole designed to mitigate the risk of foot ulcers—a common complication of diabetes that can lead to severe consequences, including limb amputation. This specialized insole incorporates photoplethysmography sensors, which are capable of measuring blood flow and oxygen saturation levels (SPO2) at various peripheral sites, including the finger, earlobe, forehead, and toe. By continuously monitoring these vital parameters, the wearable shoe aims to provide early detection of compromised blood circulation and reduced oxygen levels in the extremities. Timely identification of such issues can facilitate proactive interventions, helping to prevent or minimize the development of foot ulcers and, consequently, reduce the likelihood of more severe complications such as infections and amputations. This technological approach exemplifies the intersection of healthcare and wearable technology to enhance the management and well-being of individuals living with chronic conditions like diabetes [3].

Technologically, an advanced healthcare system that combines deep learning and IoT for the early detection of blindness using retina images. The integration of these technologies reflects a growing trend in developing innovative solutions for proactive and personalized healthcare. Blindness detection is to detect blindness or potential eye diseases by analyzing retina images. Retina images can provide crucial information about the health of the eyes and abnormalities or patterns of blindness or specific eye conditions can be identified through advanced image processing and deep learning algorithms. The use of deep learning and IoT in this context could lead to more accurate and efficient detection of eye conditions. Timely detection and intervention can significantly impact the condition of eye diseases. The implementation of such systems may face challenges related to data privacy, the need for robust and diverse datasets for training deep learning models, and ensuring the reliability of IoT devices for health monitoring.

The classification of diabetic retinopathy involves assessing the severity of the condition based on retinal images. Severity levels are often categorized on a scale (e.g., from mild to severe) to aid in treatment decisions. Many recent studies leverage deep learning techniques for diabetic retinopathy classification due to their ability to automatically learn relevant features from images. Convolutional Neural Networks (CNNs) have been widely used for image classification tasks, including diabetic retinopathy. Attention mechanisms in neural networks help focus on specific regions of input data, allowing the model to give more weight to important features.

GCA: Global Context Attention (GCA) mechanisms aim to capture long-range dependencies and global information in the input data. Attention mechanisms can be applied to highlight significant regions in retinal images that contribute to the diagnosis. Some studies specifically incorporate Global Context Attention mechanisms for diabetic retinopathy severity classification. GCA mechanisms may help the model consider the global context of the retinal image, potentially improving accuracy in distinguishing between severity levels. Evaluation metrics commonly used in this context include sensitivity, specificity, and accuracy. Challenges in diabetic retinopathy classification include dealing with imbalanced datasets, interpretability of deep learning models, and ensuring robustness across diverse populations. Future directions may involve exploring the explainability of attention mechanisms, transfer learning, and the integration of multimodal data.

Luminance approach: Cataracts are a leading cause of permanent blindness, emphasizing the spread and the need for timely treatment. Existing methods for cataract detection using smartphones exhibit sensitivity to device variations and environmental conditions. To overcome this, a luminance-based approach for cataract diagnosis, demonstrating its robustness across different smartphone models has been introduced.

SVM: A Support Vector Machine (SVM) classifier is employed for distinguishing healthy and diseased eyes. Validation using various iPhone models offers independence from sensor characteristics and environmental changes.

Saliency Consistency: It involves methods and approaches related to color blindness, image recoloring, and saliency consistency. Color Vision Deficiency, people with color blindness perceives colors differently due genetic disorder affecting the photoreceptors in their eyes. The most common type is red-green color blindness. The goal of image recolorization is to adjust the colors in images so that individuals with color blindness can distinguish and perceive the content more effectively. It follows the 3 steps image analysis, color adjustment, and consistency preservation. Saliency maps play a crucial role in this process. These maps highlight areas of an image that are visually more significant [4].

ETA: Wearable Obstacle Avoidance Electronic Travel Aids for Blind and Visually Impaired Individuals are innovative devices designed to enhance the mobility and independence of people with visual impairments. The primary goal is to assist blind and visually impaired individuals in navigating their surroundings safely by detecting obstacles and providing real-time feedback. Aids are typically designed to be worn by the user, such as on the head, waist, or chest, allowing for hands-free operation and integration into the user's daily routine. Obstacle Detection Sensors incorporate various sensors like ultrasonic sensors, infrared sensors, or computer vision cameras to detect obstacles in the user's path. Ultrasonic sensors can measure the distance to objects by emitting ultrasonic waves and analyzing the reflected signals. Infrared sensors can detect obstacles based on the reflection of infrared light. These aids can be tested on visually impaired individuals rather than healthy people [5].

II. REVIEW OF METHODOLOGIES

Data Collection and Preprocessing: Gather a large dataset of retina images, including images from individuals with and without various forms of retinal diseases. Preprocess the images to ensure uniformity in size, resolution, and quality and increase the diversity of the dataset. It involves techniques like rotation, scaling, cropping, and flipping. An IoT infrastructure can securely collect retina images from patients.

A real-world eye disease image dataset is utilized, comprising high-resolution retina images captured through fundus photography under diverse imaging circumstances. The dataset includes 5,590 images labeled for diabetic retinopathy severity on the ICDR scale (0 to 4). The severity classes range from 'No DR' (0) to 'Proliferative DR' (4). The dataset is split into training (3,662 images) and test sets (1,928 images), with imbalances observed, particularly in the 'No DR' class. Images are of substantial size (2,896 × 1,944 pixels). The dataset exhibits noise, with artifacts like out-of-focus, overexposed, or underexposed images, reflecting variations across clinics and cameras over an extended period.

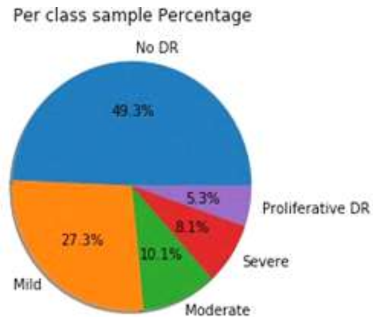

Figure 1. Class distribution

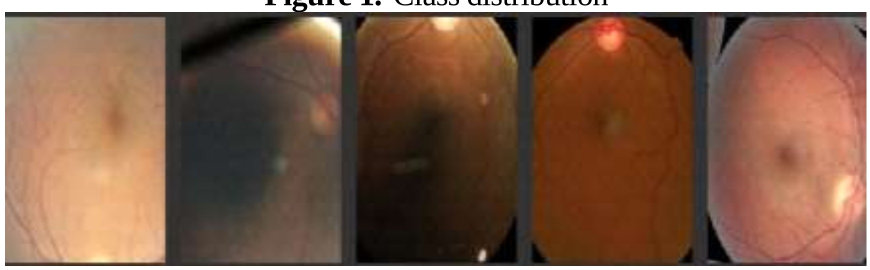

Figure 2. Typical augmentation-resize and crop

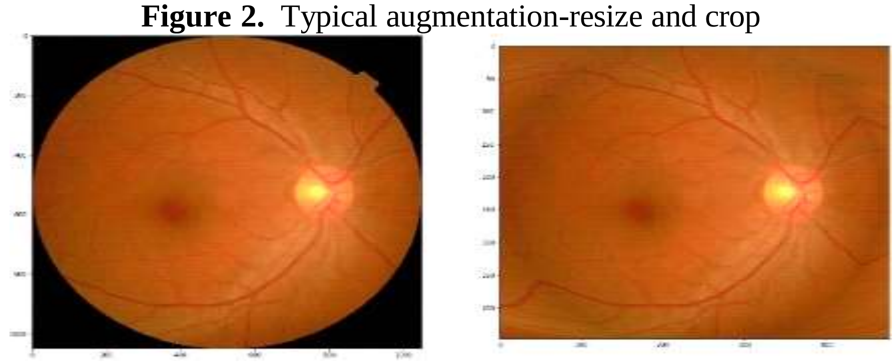

Figure 3. Sample images after augmentation

Data Augmentation: To enhance the generalization of the processed dataset for blindness detection, various augmentation techniques are applied. Using the Albumentations library, images are flipped horizontally and vertically, rotated to 360 degrees, zoomed to 1.3x, and contrast-adjusted. An auto crop eliminates black regions, determining the circle's radius, and polar unrolling facilitates rotation without the need for augmentation. This technique, along with other augmentations, improves upon existing methods for processing imbalanced data and training EfficientNet models. Additionally, an oversampling technique is explored to address data imbalance, comparing its effectiveness with Polar Unrolling. Notably, the oversampling strategy after partitioning the training dataset yields no duplicate images, ensuring proper oversampling of the retina images dataset. Mixup, a data augmentation technique, is combined with oversampling for improved generalization of detection results.

Training and Validation: The efficientNet-B5-based model is trained with a batch size of 32 for 5 epochs. Test-time augmentation is implemented during inference, and the model is cross-validated using 5 folds. Additionally, TTA is performed 10 times, and the average of 5 models is taken for evaluation. Mean squared error is used as the loss function for training the models, and the mean squared error is optimized to improve the quadratic weighted kappa score. The training data is augmented to increase the robustness of the proposed model, including rotation and flipping of the data, as well as normalization

GCA Attention Mechanism: It models the human brain's attention system by assigning attention weights to different factors, emphasizing their impact on model results. It has found widespread applications in various deep learning tasks, including sequence-to-sequence tasks, image localization, image understanding, and lip translation. One approach to attention mechanisms is the "Squeeze-and-Excitation" (SE) structure. The ECA mechanism adopts an adaptive convolution kernel size adjustment method, effectively capturing the intrinsic correlations between feature map channels. This approach mitigates the parameter increase associated with SE while maintaining an efficient inter-channel attention mechanism. The GCA structure involves a global average pooling operation to extract features, followed by an adaptive one-dimensional convolution to capture inter-channel correlations. Attention mechanisms, including SE, ECA, and GCA, play crucial roles in enhancing the performance of deep learning models, particularly in computer vision tasks. The evolution from SE to ECA represents a trade-off between performance and complexity, while GCA aims to provide a comprehensive solution that considers global channel correlations without significantly increasing the model's parameters.

GENET Structure: GCA employs a two-step process to extract global channel correlation information. Firstly, it utilizes adaptive one-dimensional convolution to derive local inter-channel correlations with a small parameter count. Subsequently, it integrates these local correlations to extract global channel correlation features through a linear operation. This approach prevents overfitting issues associated with a large number of parameters, making the model more robust. The GCA structure's effectiveness is highlighted in the context of disease severity classification, where a model based on GCA is proposed and trained using transfer learning.

Data Acquisition: Data acquisition involved using an Axis Scientific 7-Part Human Eye model to simulate healthy and diseased eyes in various environmental conditions. Images were captured using iPhone X, iPhone 6, and iPhone 11 Pro cameras. The camera settings included LED flashlights, autofocus, and maximum resolution. Subjects maintained a stable head and eye position, aligning their eyes with the smartphone's rear camera positioned 10 cm to 50 cm away. A total of 100 eye model images were captured, 50 from healthy models and 50 from models emulating different cataracts. The diseased eye models featured various cataracts, including posterior subcapsular, cortical, nuclear, mature, and capsular cataracts. Different environmental factors were diversified to assess their impact on image features, including ambient lighting, distance between the camera and eye model, camera angle relative to the eye model, and smartphone camera characteristics. The effects of each environmental factor, four main phases of validation were conducted, each constraining other factors while changing one. These phases involved varying ambient light intensity, distance, camera angles, and smartphone types. Ambient light conditions were precisely measured using dimmable lights and a color Muse device in a controlled dark room. The data acquisition strategy aimed to investigate the influence of environmental factors on image features, providing a robust dataset for subsequent analyses in the study.

Luminance Calibration: To account for variations in camera sensor characteristics and flashlight specifications among the three different smartphones used in the study, a calibration process was implemented. This involved measuring the maximum luminance emitted from an identical smartphone's flashlight and using it as the reference standard. To minimize the impact of ambient light and ensure accurate calibration, a specially designed 3D-printed gadget with light-absorbing properties was utilized. The calibration procedure included adjusting the flashlight power on each smartphone to achieve a controlled and consistent level of emitted light. The flashlight intensities for iPhone 6, iPhone X, and iPhone 11 Pro were measured at 112, 136, and 154 lumens, respectively. To standardize the flashlight intensities across all smartphones, they were adjusted to emit 100 lumens using the respective smartphone's flashlight tuning application. This meticulous calibration process aimed to ensure uniformity in flashlight characteristics across different smartphones for reliable and accurate image analysis.

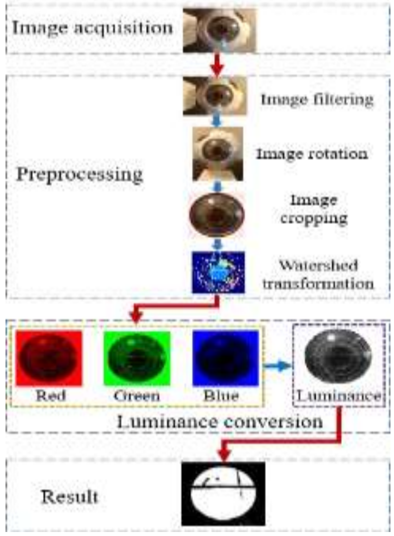

Figure 4. Flowchart for detecting cataracts using the luminance-based method

Watershed Transform: Watershed Transform is used to detect the cataract because most cataract diseases appear in the shape of a circle in the lens area, the watershed algorithm can be applied for image segmentation and visualization of the diseased areas.

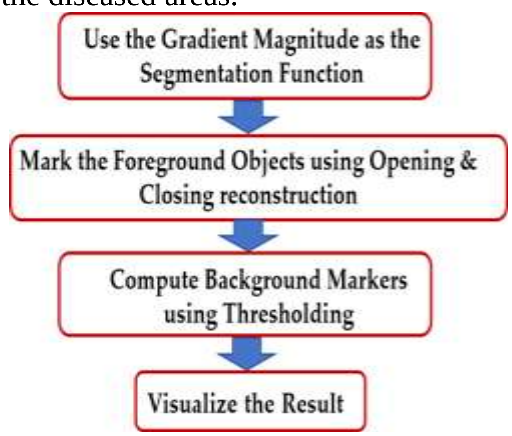

Figure 5. Watershed algorithm flowchart

Color Blindness Simulation: The human retina comprises two main types of cells: cone cells and rod cells. Cone cells, concentrated in the fovea centralis, are active in normal lighting conditions, with 5 to 7 million cells per region possessing enhanced resolution and the ability to sense brightness and color. Rod cells, numbering between 75 and 150 million outside the fovea centralis, are more light-sensitive and function in low light. While rod cells contribute to color perception, they heavily rely on cone cells. Human color vision relies on three light-sensitive pigments (L-, M-, and S-cones) in a trichromatic system, with different wavelengths stimulating receptors in varied ways. Destruction or dysfunction of any cone cell leads to color vision defects. To aid colorblind individuals, colorblind image simulations have been developed using various methods, such as spatial transformation, color space conversion, and neural networks, allowing for improved perception of surroundings.

Image retrieval: With advancements in screen display technology, users now have access to a wide array of images and videos. To facilitate efficient retrieval of multimedia data, image retrieval technology has been developed, allowing users to swiftly and accurately find images based on their specific needs. Deep learning has played a crucial role in the significant progress of image retrieval, leading to applications in product search, face recognition, and image geolocation. The evolution of image retrieval began with text-based methods like Page-Rank, but drawbacks such as manual labeling and subjective text descriptions prompted the emergence of content-based image retrieval (CBIR). CBIR utilizes low-level features like color, texture, and shape, calculating similarity to filter and retrieve relevant images. Overcoming limitations in visual features, semantic-based image retrieval (SBIR) integrates natural language processing and traditional image retrieval techniques. Convolutional neural networks, dictionary learning algorithms, and capsule networks contribute to this evolution. The process has transitioned from text to visual content, and now to semantic-based retrieval, emphasizing the extraction and comparison of relevant attributes for desired image retrieval.

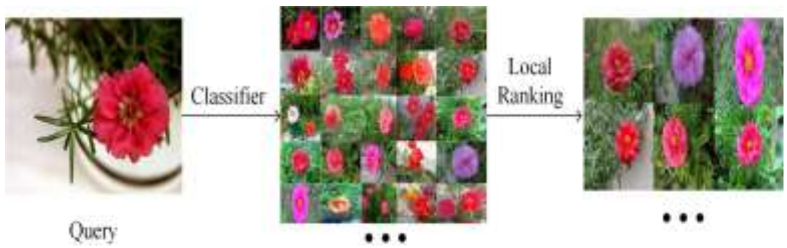

Figure 6. Image retrieval

Saliency Detection: The rapid growth of multimedia technology has led to a proliferation of images with varying quality, necessitating efficient methods for filtering and identifying relevant information. Leveraging computers to emulate human vision, visual saliency research has become a focal point in multimedia technology. This research aims to replicate human visual perception and attention mechanisms, enabling automatic prediction, localization, and extraction of important information from images. With the advent of deep learning, attention models, inspired by human attention mechanisms, have been integrated into neural networks. These models address challenges in computer vision by analyzing context information. Saliency detection models, utilizing local and global contrast, background cues, and convolutional neural networks (CNN), have achieved success. In the realm of complex images, co-saliency detection methods characterize main content by identifying common saliency regions across multiple related images. This involves extracting effective features, using information clues to characterize saliency, and calculating common saliency areas. The methods include low-level features like color histograms and Gabor filters, as well as utilizing saliency regions from individual images for detecting co-saliency across the entire image collection.

Grayscale Image colorization: Grayscale image colorization is the process of adding color to a black-and-white image, commonly used in photo refurbishment and medical image recoloring. Methods include user-assisted coloring, automatic coloring, and reference image-based coloring. User-assisted methods involve manual marking of colors or color migration areas, while automatic methods use machine learning or statistical approaches. Reference-based coloring uses a similar image for input and recolors the target image based on pixel-level attributes. However, differences between the target and reference images can lead to errors in feature-based coloring. The proposed framework in Figure 2 involves generating an image collection, detecting saliency maps, and recoloring saliency-changed images. Automatic coloring with convolutional neural networks may lead to issues like out-of-bounds color and blurring in the edge area due to the ill-conditioned nature of the problem.

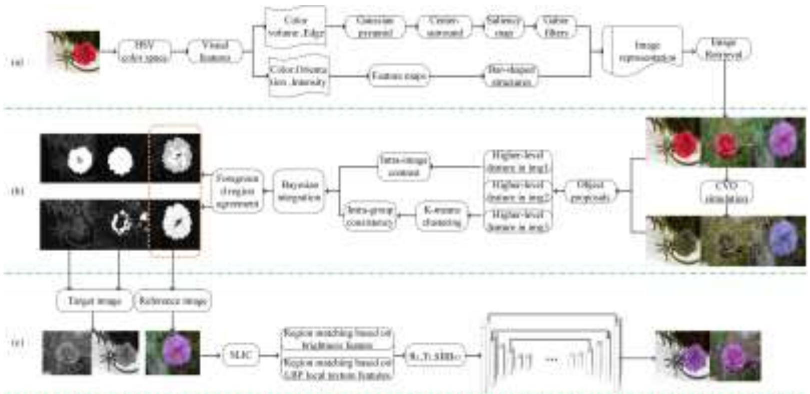

Figure 7: Grayscale Image Colourization

Data computing and system control: The processor serves as the central component, acting as the "brain" of the device, responsible for managing all operations of the sensor node. Its role involves overseeing sensor node activity while adhering to energy consumption, size, and cost constraints. Out of 59 studies, 23 utilized a single processor for both data calculation and system control, while 23 studies employed two control modules for these tasks. Seven studies did not provide information on the processor. Various types of processors were identified, including laptops, microcontrollers, portable computing units, and others. Portable computing units and embedded systems were the most commonly used across devices. Laptops served as computing and control cores in 21 studies, while 18 studies utilized microcontrollers, with the Arduino series being a popular choice. Raspberry Pi and Nvidia Jetson were also prevalent, with the latter offering advanced AI capabilities. Additionally, smartphones were implicated as processors due to their integration and computing power, often leveraging cloud services for data calculation through a local module with internet access. The diversity in processor choices reflects the varied requirements and preferences in different studies.

Figure 8. Different positions in the body

Environmental detections: Environment detection techniques, including ultrasonic sensors, cameras (especially the RGB-D camera), LiDAR sensors, infrared sensors, laser sensors, 3D CMOS image sensors, and Time of Flight sensors for obstacle detection. Seventeen studies explored combinations of two or more techniques. Computer vision-based technology, particularly cameras, emerged as the most popular, with the RGB-D camera being favored in 20 studies. Ultrasonic sensors were also frequently chosen for their cost-effectiveness and high accuracy in obstacle detection. Notably, two studies integrated LED visual modules for passive obstacle avoidance, in addition to active obstacle avoidance functions, to warn pedestrians and enhance safety.

Human-computer feedback: Out of the 42 devices studied, 22 of them used individual acoustic notifications like voice commands or guidance to provide feedback. On the other hand, 20 devices used a single acoustic alarm or signal like buzz, music, or natural sounds. Additionally, 21 devices had independent haptic vibration, while 22 devices used a combination of acoustic and tactile feedback. Some devices used transcutaneous electro-neural stimulation as a feedback mechanism, while others used a braille display interface. One of the devices combined braille displays with haptic vibrations to enhance the feedback effect.

PPG Sensor: A PPG sensor, or Photoplethysmogram sensor, is an optical device designed to measure changes in blood volume in peripheral blood vessels. Mainly used for monitoring heart rate and cardiovascular parameters, PPG sensors operate based on photoplethysmography. This method entails measuring variations in light absorption caused by changes in blood volume. These sensors commonly utilize light-emitting diodes (LEDs) and photodetectors to capture and analyze this data, providing valuable insights into physiological conditions.

Wireless data transmission: It is the process of sending and receiving data without the use of physical cables or wires. This technology is crucial in communication systems and networks, providing increased flexibility and mobility. In the medical context, the Perfusion Index (PI) is calculated from the alternating current (ac) and direct current (dc) components of the photoplethysmography (PPG) signal. The PI serves as a metric for pulsatile blood flow relative to non-pulsatile static blood flow in peripheral tissues, offering valuable insights into vascular health. The recorded PPG signals underwent thorough processing for feature extraction, encompassing time intervals, AC and DC components, and pulse area of the pulsatile signal. Using a dataset derived from the 20 test subjects, machine learning (ML) techniques, including multiple linear regression and classification methods, were applied to predict SpO2 levels and identify the measurement site (either finger or toe). The ML outcomes underscored the significant role of AC components in PPG signals in accurate SpO2 estimations, emphasizing their importance over DC components in predictive modeling. The durability of the flexible and wearable smart shoe insole, which incorporates an oximeter, through a cyclic bending test aimed at assessing its reliability and robustness over multiple uses. During this experiment, the focus was on measuring the resistance change in a pair of four copper traces at specific locations connecting to both the PPG sensors and the microcontroller. This evaluation aimed to gauge the insole's ability to withstand repeated bending, simulating real-world conditions and ensuring the device's longevity and performance consistency.

Figure 9. Prototype of the wearable boot device for at-home monitoring of the diabetics' foot ulcers via continuous measurement of the ulcers' saturated oxygen and electrical stimulation treatment [6].

III. RESULTS & DISCUSSIONS ON REVIEWED WORK

This work represents the cutting-edge technologies used for detecting blindness in eye diseases like DR using retinal images & IOT framework. The efficient B5 model surpasses CNN and RESNet-50 models, achieving 92.32% accuracy in identifying the severity of DR. Oversampling strategies are also followed for better interpretations noticing that 89% of images showed no symptoms or moderate retinopathy. This approach is specifically designed for early DR detection in diabetic patients. The training process uses transfer learning and cosine annealing techniques. The final GE-Net model attains high accuracy, precision, sensitivity, and specificity (0.956,0.956,0.956, and 0.989) on the DR validation set. Thus proved the efficiency of the GCA mechanism. So that we can combine GCA with other deep-learning models to detect slight differences between categories. Detecting cataracts using smartphones is an affordable, rapid, and versatile approach. Many smartphone-based cataract detection methods exhibit different accuracies. However, a luminance-based method accommodates different smartphone camera sensors and chroma variations while remaining unaffected by color characteristics or changes in distances and camera angles. A saliency consistency-based image recolorization technique is introduced. This process involves image collection, CVD simulation, performing saliency, and selecting a reference image to recolor remaining images whose salient areas are changed. So it makes the same color distribution on the reference as well as on the remaining images which bridges a gap in color perception between color blind and normal-vision individuals. Different processors, environment detection methods, and human-computer feedback are very challenging to determine the effective one. To optimize obstacle avoidance, we can combine multiple detection techniques and feedback into a single system but it can lead to hardware demands causing issues like high latency, power consumption, etc. Conducting user experience tests with visually impaired people rather than sighted volunteers with some vision can have accurate results.

IV. CONCLUSION

This work presents a cutting-edge deep learning-based smart health system designed for identifying blindness in eye diseases, specifically diabetic retinopathy. The system utilizes an Internet of Things (IoT) framework and demonstrates that the integration of IoT and artificial intelligence (AI) can result in an effective smart health system. The researchers fine-tuned an Efficient-B5-based model and compared its performance with CNN and ResNet50 models. The fine-tuned Efficient-B5 model achieved a superior 92.32% validation accuracy, outperforming the other models. This model predicts the severity of diabetic retinopathy, a condition leading to eye blindness, on a five-point scale using retinal images. The baseline model, also based on Efficient-B5 and trained on average doctor opinions, showed state-of-the-art results with 90.20% validation accuracy in identifying blindness. Additionally, the study implemented freezing and unfreezing techniques during the fine-tuning process, significantly improving predictions with 92.32% validation accuracy. The research focuses specifically on early detection of diabetic retinopathy in diabetic patients and employs oversampling strategies for result interpretation. It's important to highlight that the proposed approach is tailored for the early detection of diabetic retinopathy in diabetic patients, and further testing is recommended before applying it to other medical image diagnoses. The study identifies a prevalence of images with no diabetic retinopathy symptoms (0's) and moderate retinopathy (2's) in approximately 89% of the dataset. Continuous monitoring of oxygen saturation levels (SpO2) at the foot of individuals with Diabetic Foot Ulcers (DFUs). This is crucial because blood flow information at the foot is essential for administering adjunctive treatments, especially in cases of low blood flow and poor wound healing. Perfusion Index (PI) measurements to validate the oximeter readings. The wearable insole integrates seamlessly with the Internet of Things (IoT) and enables "at-home" monitoring.

V. REFERENCES

[1] A. K. Jaiswal, P. Tiwari, S. Kumar, M. S. Al-Rakhami, M. Alrashoud, and A. Ghoneim, "Deep Learning-Based Smart IoT Health System for Blindness Detection Using Retina Images," IEEE Access, vol. 9, pp. 70606-70615, 2021, doi: 10.1109/ACCESS.2021.3078241.

[2] B. Yang, T. Li, H. Xie, Y. Liao and Y. -P. P. Chen, "Classification of Diabetic Retinopathy Severity Based on GCA Attention Mechanism," IEEE Access, vol. 10, pp. 2729-2739, 2022, doi: 10.1109/ACCESS.2021.3139129.

[3] B. Askarian, P. Ho and J. W. Chong, "Detecting Cataract Using Smartphones," IEEE Journal of Translational Engineering in Health and Medicine, vol. 9, pp. 1-10, 2021, doi: 10.1109/JTEHM.2021.3074597.
[4] J. Li, X. Feng and H. Fan, "Saliency Consistency-Based Image Re-Colorization for Color Blindness," IEEE Access, vol. 8, pp. 88558-88574, 2020, doi: 10.1109/ACCESS.2020.2993300.
[5] P. Xu, G. A. Kennedy, F. -Y. Zhao, W. -J. Zhang and R. Van Schyndel, "Wearable Obstacle Avoidance Electronic Travel Aids for Blind and Visually Impaired Individuals" IEEE Access, vol. 11, pp. 66587-66613, 2023, doi: 10.1109/ACCESS.2023.3285396.
[6] M. Panahi et al., "A Smart Wearable Oximeter Insole for Monitoring SpO2 Levels of Diabetics' Foot Ulcer," IEEE International Conference on Flexible and Printable Sensors and Systems (FLEPS), Vienna, Austria, 2022, pp. 1-4, doi: 10.1109/FLEPS53764.2022.9781511.