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Smartphone-Based Machine Learning for Automated Diagnosis Using Eye, Skin, and Voice Signals

Shaikh Abdul Hannan
Assistant Professor, Faculty of Computing and Information, Al-Baha University, Al-Baha, Kingdom of Saudi Arabia
abdulhannan05@gmail.com

Abstract*−Applying machine learning techniques to data produced by commonplace gadgets like smartphones offers a chance to improve the standard of medical treatment and diagnosis. Smartphones are perfect for collecting data, giving prompt feedback on diagnosis, and suggesting measures to enhance health. Cloud-based Internet of Things (IoT) apps provide smart cities with cutting-edge ways to reduce traffic accidents brought on by fatigued driving. In this work, we examined cutting-edge methods for identifying risky driving behaviors utilizing three popular IoT-based systems. Effective treatment requires an early and precise diagnosis. Artificial Intelligence (AI) has recently demonstrated encouraging possibilities in helping physicians diagnose pterygium. An overview of AI-assisted pterygium diagnosis is given in this work, along with information on the AI methods that are employed, including computer vision, deep learning, and machine learning. Dehydration is brought on by the body losing fluids, which interferes with normal bodily processes and leads to health issues. The current methods for detecting dehydration in clinical and laboratory settings are costly, time-consuming, and need visiting medical facilities, which are frequently absent in impoverished areas. We create a deep learning model based on Siamese networks to identify changes in facial features caused by dehydration that are invisible to the average person. Our model is light enough to operate on a smartphone processor and has an overall accuracy of 76.1%. By integrating it into the backdrop, we create a smartphone app called "Dehydration Scan" that merely takes pictures of people's faces and determines how hydrated they are. People can use oral rehydration solutions and prevent severe dehydration if they are aware of dehydration early on.

Keywords:-* *Rehydration Solutions, Human Body, Smartphones Presents, Laboratory-Based, Facial Landmarks, Hydration Status, Deep Learning Model.

I. INTRODUCTION

In addition to a decrease in neuron size, there is a noticeable decrease in the number of connections between brain cells as people age. Nerve cells have a restricted ability to regenerate, in contrast to muscle, skin, and bone cells. Neuronal death or damage has been found to occur more often as people age, according to earlier studies.

Machine learning is increasingly being used for medical diagnostics. The availability of a large amount of health data and advancements in the categorization and identification algorithms used in illness diagnosis are the main causes of this. Machine learning models may be developed using the wealth of health-related data produced by the healthcare sector. Numerous illnesses, including as diabetes, heart disease, and breast cancer, may be identified and predicted using these models (Ngai, E.C.H.; Leung, V.C. et al. 2016). According to the emphasis on various characteristics (biomarkers), the prognosis of these illnesses depends on multiple variables. The use of machine learning techniques makes it simpler to categorize and diagnose illnesses. These diagnoses can assist medical professionals in identifying deadly conditions early on, thereby improving patient survival rates and the quality of healthcare.

Because methods for machine learning and their applications are not restricted to certain data types, they have been utilized in a wide range of fields, including the detection of spontaneous abortion, the identification of intricate patterns in brain data, the improvement of diagnostic precision, and the detection of axial pump defects. Using publicly accessible datasets, such as the UCI machine learning library, the National Health and Nutrition Examination Survey (NHANES), Traumatic Brain Injury (TBI), and SUITA datasets, machine learning techniques have also been used to diagnose and forecast different illnesses (Pratt, S.G.; Bell, J.L. et al. 2019). In a similar vein, a plethora of smartphone-based medical applications have been created to assist healthcare professionals and the general public with their health-related issues. The apps created may be roughly categorized into three distinct user groups: patients, medical/nursing students, and health care professionals.

A commonly used neuroimaging technique is electroencephalography (EEG), which records and analyzes the electrical activity of the brain by affixing electrodes to a subject's scalp. These electrodes capture voltages produced by the brain's localized activity in neurons. By examining these voltage patterns, researchers can get insight into a number of aspects of brain activity and function. For researchers studying neurological disorders, sleep science, and cognitive neuroscience, the EEG has proven a priceless tool. Non-invasive electronic devices have been widely used in medical examination for a variety of conditions, including epilepsy, sleep disorders, and sensory transmission. Because there are noticeable and significant variations in EEG patterns across a range of illnesses, skilled neurophysiologists are able to evaluate and comprehend the underlying medical conditions in a subjective and relative manner. Subtle changes have been observed in certain neurological conditions. However, human observers and current assessment techniques may find it challenging to accurately assess the importance of these variations because of the complexity of EEG data (Soua, R.; Karray, F.; et al. 2017). The use of EEG to diagnose Alzheimer's, brain tumours, and Parkinson's

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Disease (PD) has shown great promise, and research into the effectiveness of Deep Learning (DL) and neural networks in this area is growing.

The Internet of Things (IoT) is a quickly expanding field of study where a lot of data is collected and processed using cloud-based and smartphone apps. Smartphones, sensors, and machines are integrated to create these IoT cloud-based applications. In order to realize the idea of smart cities, the authors are creating a novel IoT-based application. Thus, IoT-based systems use cloud-based architecture and sensor-based smartphones to create smart cities. In reality, IoT-based apps provide creative ways to reduce fatigue-related road accidents.

Even experienced drivers are finding it increasingly difficult and confusing to drive on highways due to population growth. Applications should be developed to assess drivers' actions and surroundings in order to raise their levels of alertness. These days, road accidents are avoided with the use of mobile, cloud-based sensor and driver behavior prediction systems. Therefore, there is an urgent need to raise the standard of safe driving and make a crucial choice to react appropriately in an emergency (Verma, S.; Krishna, C.R. et a l. 2017).

The design of intelligent transportation systems heavily relies on the ability to predict driving behavior. The surroundings, driver behavior, and the vehicle itself were shown to be the primary causes of traffic accidents. These systems aid in improving the efficiency and safety of drivers. Driving behavior detection is a developing field of study since improper driving conduct is the primary cause of accidents. Leading manufacturing firms have developed and effectively deployed a number of driver sleepiness and distraction strategies in previous research. When collecting vast volumes of driving data, driver behavior analysis is crucial. Numerous algorithms employ smartphone apps to collect data in real time and anticipate behavior (Birch M, Shah N, et al. 2018). Several hardware elements, including a mobile camera and sensors, were employed in those investigations. Global Positioning System (GPS), accelerometer, and gyroscope data are gathered by sensors in order to identify important trends. Multimodal feature-based Driver Fatigue Detection (DFD) systems are created by combining driving behavior characteristics. After classifying the data, the researchers used machine learning techniques to predict driver fatigue (Xu YW, et al 2023). Figure 1 shows a broad visual representation of the multimodal feature-based driver tiredness detection systems.

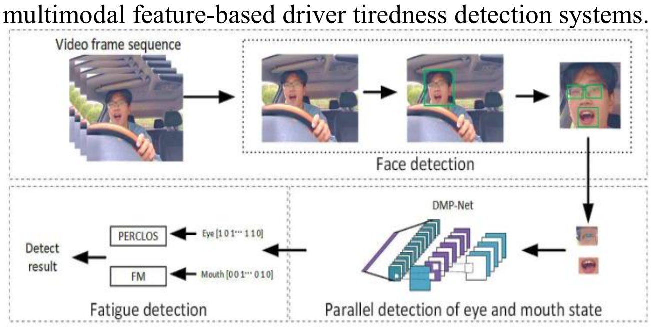

Fig. 1 A diagram of the multimodal characteristics for identifying driver weariness.

Recent apps that used cloud-based architecture to improve the accuracy of sleepiness prediction have created multi-sensor and smartphone-based algorithms. In reality, cellphone can readily identify four distinct patterns (braking, accelerating, left cornering, and right cornering) using an inexpensive solution. In order to install applications in smart-aware cities, commercially available wearable apps transform mobile devices into centers for data collecting. As a network cluster for analyzing power and information sources in IoT-based design, many users were taken into consideration in many previous systems. Smartphones and wearable sensors are currently being utilized to collect physiological big data for highway accident prevention and early prediction (Guoji Yanke Zazhi et al. 2023). Numerous writers created computer-based solutions for the evaluation of driver state, driving context, and performance using cutting-edge hardware, mobile devices, or built-in cars in cloud-based settings. These days, smartphone-based apps are far more common than older methods as it is quite simple to gather data on drivers using mobile or hardware-based sensors and cameras.

The most widely used imaging equipment in ophthalmology have developed into vital instruments for clinical eye care, and imaging plays a crucial role in the diagnosis and treatment of eye diseases. However, these gadgets are usually costly, immovable, and require skilled workers to take good pictures. Clinicians now have a chance to increase access to care thanks to the widespread availability of smartphones and their growing computational capacity and camera quality (Arnould L, Mouriaux F. et al. 2022). Previous research has looked into using smartphones as a platform for ophthalmic testing and data collecting for activities including retinal and anterior segment imaging, color perception testing, and visual acuity testing. Using smartphones as a platform for ophthalmic telemedicine might be an affordable method of providing care to underserved or rural places. Smartphone-based image acquisition has been previously documented for anterior segment imaging, and patients can use their own devices to get high-quality pictures. These solutions usually entail an optical attachment of some sort to enhance image quality or facilitate capturing. However, the ability to take usable photos without the need for further equipment or accessories is made possible by improving smartphone camera quality and computational techniques to filter or enhance photographs.

When the amount of fluid in the human body drops below a specific point, dehydration happens. Dehydration is a major cause of death globally since it is a common side effect of numerous illnesses, including cholera, fever, and diarrhea. People, particularly in underdeveloped nations, become sick with waterborne illnesses like cholera and diarrhea due to inadequate sanitation and safe drinking water. The majority of individuals don't recognize their dehydration until it's too late. Hospitalization becomes necessary by that point.However, neither the hospitals nor the majority of these individuals have the financial means to offer quality medical treatment in the underprivileged communities. As a result, a rise in the number of fatalities is unavoidable

(Brona P, Lim G, et al. 2022). These situations do occur in the industrialized world as well, albeit they are more common in lower-income nations. Mild to severe dehydration can also occur in people as a result of inadequate fluid intake or physical activity. Research indicates that minor dehydration affects mood, alertness, focus, and cognitive function. Given the numerous direct and indirect impacts of dehydration on the human body and mind, a widely accessible diagnostic method is now required.

Our facial landmarks are subtly altered by dehydration, particularly in areas like the lips and eyes (e.g., diminished skin turgor or elasticity, weary and dry eyes, dry lips). Human eyes frequently fail to notice these alterations, particularly in the early stages of dehydration. As a result, even though it is a common ailment, it frequently goes unrecognized. In this instance, we use artificial intelligence to overcome the limits of human eyesight (Yang Q, Zhang RH, et al. 2021).

The absence of a dehydration dataset that meets our requirements and is publicly accessible is one of the biggest obstacles we confront. In order to address this problem, we create our own dataset of 2340 sample pairs of photos from 70 healthy volunteers that are either hydrated or dehydrated. To prevent the inference of other diseases on the facial landmarks, we do not include participants in the dataset who have any other illnesses. According to research, people often experience minor dehydration during fasting. For the purpose of gathering statistics, we take into account the month of Ramadan, when devout Muslims fast from dawn to sunset. We create a data gathering application to take participants' faces while they are both hydrated and dehydrated. Next, we use our pre-processing methods to extract the pictures of the face landmarks, enhance the image quality, and eliminate image noises. The lips, eyes, and surrounding areas are among the landmarks that exhibit the most noticeable alterations when dehydrated. Our final dataset, which we use to train and evaluate our model, consists of pre-processed images of various locations.

A. Objectives of the study

- To create and assess a smartphone-based machine learning system that can automatically diagnose diseases by examining multimodal signals from the voice, skin, and eyes.
- We develop preprocessing techniques to extract certain face landmarks from the picture frames and eliminate noise brought on by various backdrop and lighting conditions.
- We create a comprehensive and useful smartphone application that allows users to snap images of their faces and instantly determine their level of hydration.

II. LITERATURE REVIEW

Huang, C. Y., Lee, Y. T., (2022) Clinicians who provide primary care for children and adolescents frequently deal with middle ear illnesses such otitis media and middle ear effusion, for which diagnosis is frequently delayed or misinterpreted. Through imaging, artificial intelligence (AI) may help medical professionals identify and diagnose middle ear disorders. From January 1, 2011 to December 31, 2019, otolaryngologists at Taipei Veterans General Hospital in Taiwan gathered and de-identified otoendoscopic images. During data pre-processing, augmentation, and splitting, the pictures were fed into convolutional neural network (CNN) models for training. Nine CNN-based models were developed to identify middle ear conditions in order to distinguish complex middle ear disorders. For usage on mobile devices, the top-performing models were selected and combined into a tiny CNN. The usefulness was assessed in terms of identifying and categorizing 10 middle ear disorders using otoendoscopic pictures after the pretrained model was transformed into a smartphone-based application.

Majumder, S., & Deen, M. J. (2019) Life expectancy has dramatically improved over the last several decades due to major advancements in medical research and technology, as well as increasing knowledge of environmental and personal cleanliness, diet, and education. As a result, it is anticipated that the number of old people in many nations would increase quickly in the years to come. The rapidly growing number of old people is predicted to have a negative impact on many countries' socioeconomic systems due to the expenses of their healthcare and well-being. Furthermore, illnesses pertaining to the skin, eyes, respiratory system, cardiovascular system, and mental health are common worldwide. However, with constant observation, the majority of these illnesses may be prevented and/or effectively treated.

Mazumder, N. (2021)It has been demonstrated that smartphone-based imaging devices (SIDs) are adaptable and have several biological uses. Technology solutions like portable gadgets that may be employed in distant and resource-poor settings have an influence on both the quantity and quality of care given the growing demand for high-quality medical services. Furthermore, smartphone-based gadgets have demonstrated their usefulness in fields including education, food technology, and tele imaging. SIDs can be employed in a variety of configurations, including bright-field, fluorescence, dark-field, and multiplex arrays with specific adjustments to their optics and lighting, depending on the application and imaging capacity required. This comprehensive discussion covers the various uses and advancements of SIDs for routine diagnostics, food technology, bacterial and viral detection, and histopathological evaluation.

Bui, T. H., Thangavel, B., (2023) Analytical chemistry and diagnosis have historically depended on wet labs and highly qualified personnel using advanced equipment for sample handling and analysis. However, there has been a notable trend toward the use of independent sensors due to the development of innovative materials and sensing techniques. This has made it possible to conduct testing on-site or even in real time, which results in reduced expenses and time. With their vast sensor capabilities, sophisticated computing power, and connectivity capabilities, cellphone have become the perfect platform for these sensors due to their ubiquitous use internationally. Both optical and electrochemical sensors are used in smartphone-based

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assays. The micro-USB port, Bluetooth connectivity, and wireless communication enable data transmission and analogue electrical applications for electrochemical sensing, while built-in cameras, ambient light sensors, and other features are used for optical sensing. This study offers a thorough analysis of current developments in smartphone-based sensors, including both optically and electrochemical sensing techniques. Previous summary studies have examined smartphone-based sensing in certain industries.

Barbé, K., & Grimaldi, D. (2015) The widespread adoption of smartphones with new built-in sensors has encouraged academics to create applications across several industries. An overview of the most important health-care applications is the goal of this study. The usage of (i) a 3D accelerometer for actimetric, body posture, and fall monitoring, (ii) a camera for assessing cardiovascular system parameters, blood oxygen saturation, and ocular pathologies, and (iii) a microphone for identifying respiratory disorders are the main areas of interest. To emphasize their advantages and disadvantages, these applications are compared to conventional medical equipment. Limitations and potential avenues for further study are discussed.

Lijiya, A. (2022) Recent technological developments have enabled computer vision (CV) researchers to offer dependable and practical services that enhance people's quality of life in a number of ways. Automation in factories, self-driving automobiles, surveillance, medical adaptive technology (AT), human-computer interaction, remote sensing, and agriculture are a few of the important uses. Significant advancements in processing power paved the groundwork for the development of effective machine learning and deep learning algorithms, which in turn enabled CV applications that would not have been conceivable previously. Because of its social commitment, AT has a unique place. Any program, product, or service that helps an aged or disabled person enhance their quality of life is considered Assistive Technology (AT). This chapter discusses AT designed for those with visual, hearing, and linguistic impairments since the variety of AT approaches available today is too much for a single section.

Chung, W. Y. (2012) In this research, a data fusion strategy based on multiple discrete data types—eye characteristics, bio-signal fluctuation, in-car temperature, and vehicle speed—is proposed to monitor driver safety levels. In actuality, the driver safety monitoring system was created as an Android-based smartphone application, which eliminates the need for additional equipment or money to measure safety-related data. Additionally, the technology offers great versatility and resolution. As a component of the security surveillance procedure, characteristics obtained from several sensors—such as temperature, photoplethysmography, video, ECG, and a three-axis accelerometer—are combined and sent to an inferences analysis framework as input variables. The driver's capability level is indicated using a fuzzy Bayesian framework that is updated in real time. Bluetooth connectivity is used to send the sensory data to the cellphone.

Zarif, M. I. I., Hasan, M., (2019) Anemia affects 5.6% of Americans, while moderate-to-severe anemia affects 1.5% of the population. There are 1.62 billion Hb illnesses worldwide. The cyan-methaemoglobin technique is a valid clinical approach for measuring hemoglobin levels, but it is not portable, findings are not accessible right away, and most patients in nations with low or middle incomes who may benefit from it cannot afford it. Frequently examinations is less than convenient when healthcare facilities and funding are available. The delay in getting answers and the resulting blood loss are specific disadvantages of this diagnostic approach when there is a serious sickness that need repeated testing. The potential benefits of a non-invasive point-of-care (POC) approach for hemoglobin assessment are evident in these many situations. For non-invasive Hb readings, commercial non-invasive POC instruments are now accessible. One or more of the following restrictions apply to the majority of these tools:1) difficult data gathering techniques; 2) intricate data analysis and feature extraction procedures; 3) portable and affordability; and 4) expensive additional modules and a lack of user-friendliness.

Washington, P. (2023) Major health issues including obesity, depression, and heart disease can be exacerbated by stress and worry. Because human emotion is subjective, it is difficult to assess it accurately using automated methods. Therefore, rather than using a "one-size-fits-all" machine learning technique, we suggest a customized prediction framework that is adjusted for every participant. We want to get such personalized information using two different methods: 1) an ecological instantaneous measurement of stress using a smartphone, and 2) Zoom calls. Selfies and ecological instantaneous evaluations of emotion will be among the data gathered from these recurring self-reports. We suggest using gamification, a recent development that includes influencing user behavior and lifestyle by introducing entertaining and captivating game aspects into non-gaming contexts (e.g., health-related chores), to increase user engagement during the data collecting procedure.

Colburn, D. A., & Sia, S. K. (2020) A growing amount of health data is being gathered and processed in decentralized settings thanks to advancements in mobile biosensors that integrate advancements in materials science and instrumentation. For instance, vital signs may be measured using semiconductor-based sensors, while biochemical indicators can be measured using microfluidic-based sensors. It might become crucial for researchers to create biosensors with the right features and specifications to perform flawlessly with related linked hardware and software as health care biological sensors are increasingly connected with smart devices. Here, present mobile health devices and new biosensor research are discussed and categorized into four different system designs that consider the data processing and biosensing tasks needed in personal wireless health devices. Additionally covered is the future of incorporating biosensors into smartphone-based healthcare systems.

III. METHOD

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There isn't yet a picture dataset of dehydrated individuals. Since our goal is to identify dehydration in its early stages and most hospital patients are very dehydrated, gathering data from hospitalized patients would not be beneficial to business.

Our goal was to create an application that will function on any mobile device, regardless of its settings and operating system (Kia Dashtipour, Kamran Arshad, et al. 2020). For this reason, we decided to design the smartphone app using the cross-platform mobile application framework Flut) [ter.

A. Dataset

In order to create an internal face footage dataset specifically tailored to our use case, we created and released the mobile application previously mentioned (Yuting Yang, Rafael Iriya, et al. 2016). By carefully removing and merging frames from the gathered movies, we created a final dataset with 2340 picture pairings. In all, seventy people volunteered for this process. There were 34 females and 36 males among them. The age range of the participants was 10 to 50. However, our sample was biased by age because a large number of them were college students. Table 1 displays the age range.

Table 1 Distribution of individuals' ages in the dataset.

Age ranges	No. of participants
10-20	13
21-30	45
31-40	8
41-50	4

B. Data processing

The automatic preprocessing procedures carried out prior to feeding our data into a framework for forecasting and training are explained in detail in this section (Kyle Smith, and Tolga Kaya. et al. 2014). Fundamentally, our model is a siamese network that learns and recognizes the distinctions among a hydrated and a dehydrated picture via contrastive losses.

We use the Laplacian variance to filter out the fuzzy photos and retain the ones with the greatest sharpness ratings (Thyagrajan, R.; Vaddavalli, P.K. et al. 2022). We eliminate the other photos and only choose those that surpass a predetermined variance threshold. To make sure no unusual photographs have leaked through, a last manual inspection is carried outFigure 2 shows an outline of the preprocessing procedures.

$$Similarity\ (A,B) = \frac{A.B}{||A||_2 \times ||B||_2} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}} \ldots\ldots 1$$

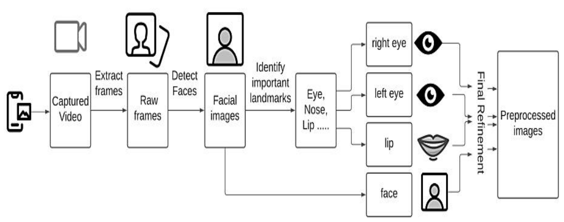

Fig. 2 Pre-processing stages.

A comprehensive graphical representation of our convolution network is shown in Figure 3 (Cohen, Y.; Mor, U.; et al. 2021). In essence, each network is a two-dimensional convolutional neural network with the same layer sequencing. Before the convolutional networks analyze the input images, a batch normalization procedure is utilized. Our approach builds the networks using a series of 2D convolutional and average pooling layers, then a dense layer with rectification linear unit (ReLU) activation and batch normalization. Next, by calculating their cosine distance, our model merges the resulting features embedded into a single layer.

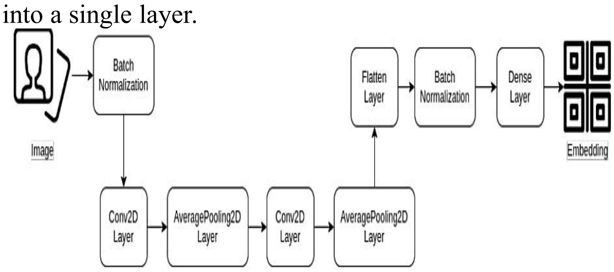

Fig. 3 Base convolutional network's layered perspective.

$$Distance(A,B) = 1 - similarity(A,B) = 1 - \frac{A.B}{||A||_2 \times ||B||_2} \ldots\ldots\ldots 2$$

Other distance metrics, such Manhattan and Euclidean distances do not yield promising results when used in the merging process (Kalra, G.; Arrigunaga, S.D.; et al. 2021). Manhattan distance is the total of the distances along each axis, whereas Euclidean distance is the straight-line distance between two vectors. In contrast to these measurements, cosine distance is dependent on the angle formed by two vectors and does not take vector size into account. As a result, cosine distance works better in our situation to distinguish between the embedded elements. The final neural network, which consists of batches of normalization and a conventional dense layer with sigmoid activation, receives the distance values that represent the contrast between the input images (Christy, J.S.; Sivaraman, A.; et al. 2021.. In summary, our suggested contrast learning framework receives pairs of photographs from the same user as input, determines how similar they are, and then generates a score between 0 and 1. Figure 4 shows the construction of this structure (Zhou H, Mao T, Liu Y. et al. 2023).

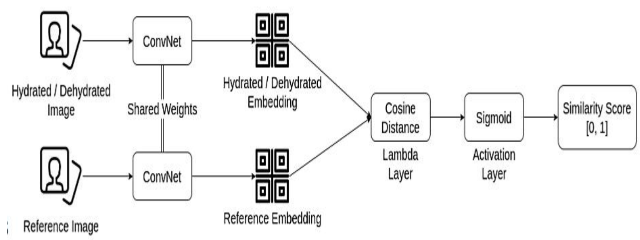

Fig. 4 A comparison learner based on Siamese networks.

For each of the image pairings of our chosen facial landmarks—the nose, lip, and right and left eyes—the contrast learner is run in parallel. In order to get the final prediction, we obtain a similarity score from each model run and compute a weighted total of those scores (Kim, J.-W.; Lee, J. et al. 2020). An thorough process of trial and error is used to determine the weight for the landmark. Following sufficient experimental research, we determine almost ideal weights to maximize prediction accuracy while taking into consideration each landmark's importance.

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Additionally, we apply the model to full facial pictures taken from video frames. To put it succinctly, in order to arrive at our system's definitive forecast, we consider every crucial area of the facial features, use our siamese network-based model to estimate individual similarities, and then aggregate the results to categorize the input image as either hydrated or dehydrated (Peek, N.; Casson, A.J.; et al. 2019). The framework of our suggested model is displayed in Figure 5.

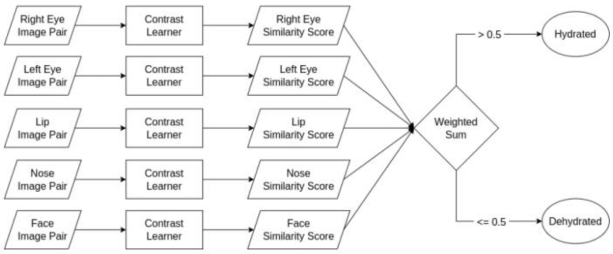

Fig. 5 Using a weighted average of scores for similarity from individual landmark images pairings for classification.

IV. RESULT AND DISCUSSION

The efficiency of our proposed dehydration detecting system is shown in this section.

We implement transferring learning to VGG16, Xception, and Resnet50 by starting the models using ImageNet-trained weights. The final predictions were then obtained by running all of the baselines on our dataset end-to-end. Next, the performance measurements and our suggested solution are compared. Table 3 offers an overview of the efficacy comparisons between the baselines and our model.

Table 3 Comparison of our proposed model's performance with various baselines.

Models	Accuracy	Specificity	Recall	F1 score
VGG16	51.89%	64.15%	85.42%	87.54%
Basic CNN	25.96%	85.54%	58.64%	28.96%
ResNet50	35.96%	22.98%	66.97%	64.25%
Our Model	54.82%	54.90%	68.95%	68.45%
Xception	69.54%	54.28%	65.89%	22.58%

We find the landmarks that exhibit changes upon dehydration in order to strengthen the contrast detection between hydrated and dehydrated states. We now go over the way each of these distinct markers works independently to identify dehydration. Table 4 displays a performance comparison of each landmark's individual achievements.

Table 4 Comparing the performance of different landmarks.

Landmark Used	Accuracy	Specificity	Recall	F1 score
Entire face	59.57%	48.96%	48.96%	49.52%
Lips	56.96%	32.56%	54.21%	54.86%
Nose	88.94%	41.85%	69.58%	51.24%
Left Eye	68.96%	99.54%	64.89%	85.62%
Right Eye	58.96%	68.75%	65.82%	33.99%
Left Eye flipped	64.85%	96.51%	54.25%	54.85%

One landmark at a time is removed and the categorization is carried out as part of ablation research. We plan to examine how each landmark affects the final categorization. Table 5 provides a summary of the ablation study's results.

Table 5 Ablation Study.

Landmark Excluded	Accuracy	Specificity	Recall	F1 score
Entire face	62.69%	78.96%	79.63%	69.54%
Lips	48.51%	48.95%	54.98%	86.95%
Nose	25.64%	66.14%	84.52%	48.96%
Left Eye	25.96%	85.96%	96.54%	25.91%
Right Eye	88.96%	25.96%	89.65%	58.96%
Left Eye flipped	64.89%	84.59%	48.96%	48.96%

In this experiment, we select the ideal number of epochs to get the highest model performance. Generally, accuracy and performance metrics increase with the number of epochs the model runs for, up to a specific point. The model's performance eventually deteriorates as it begins to overfit to the training dataset. The ideal epoch number that yields the greatest results without causing overfitting must be determined. By altering the number of epochs, Table 6 and Figure 6 provide us with a summary of the performance measurements.

Table 6 Comparison of performance over different epoch numbers.

No. of Epoch	Accuracy	Specificity	Recall	F1 score
5	69.5%	69.41%	59.48%	74.58%
8	48.58%	56.4%	96.48%	95.62%
10	45.69%	28.96%	52.63%	36.95%
12	58.9%	77.89%	28.69%	97.85%

The studies we conducted to determine the best split for the test, validation, and train sets are shown in this section. On the one hand, expanding the size of the train set provides our model with more training data, hence improving performance. Overfitting the train set is a problem, nevertheless, if the validation set is kept with minimal data. We do multiple runs with various split ratios in order to get the ideal balance, as shown in Table 7.

Table 7 Comparison of performance across different Train-Test ratios.

Train %	Validation%	Test %	Accuracy	Specificity	Recall	F1 score
60%	10%	15%	62.1%	30.2%	93.6 %	73.1 %
70%	20%	20%	63.2%	49.5%	91.5 %	75.9 %
70%	15%	15%	61.2%	38.9%	71.8 %	60.6 %
80%	20%	20%	63.6%	52.9%	98.9 %	80.9 %

The performance parameters of the male and female participants are contrasted in this section. Table 8 presents the results. Our model was trained and tested solely on male data to get the findings for male participants. For the female volunteers, we went through the identical procedure again. There is a discernible variation in the specificity and recall levels even if the accuracy is quite equal in both situations. This suggests that gender differences may exist in our model's performance.

Table 8 Comparison of the male and female contestants' performances.

(Gender)	Accuracy	Specificity	Recall	F1 score

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Male	78.9%	95.8%	98.52%	79.64%
Female	84.8%	86.9%	48.96%	69.48%

Here, we use one or more reference photos to compare our model's performance. When there was just one reference image, we matched it with every photograph of the same person that was both hydrated and dehydrated. In a similar manner, we linked each reference image with each remaining hydrated and dehydrated picture after choosing many hydrated photos for a user based on their sharpness. Table 9 shows the comparison of performances.

Table 9 Comparison of the signal's performance with many reference images.

No. of References	**Accuracy**	**Specificity**	**Recall**	**F1 score**
1	89.65%	54.62%	47.85%	58.96%
2	25.98%	54.89%	96.54%	48.25%
3	48.96%	68.95%	48.96%	96.58%

We divided information into five non-overlapping folds or subsets, and we ran our model five times for cross-validation. Each time, we used the remaining data for training and validation and selected a distinct subset for testing. Table 10 displays the average performance as well as the results from the various experiments.

Table 10 Results of a five-fold cross-validation.

No. of References	**Accuracy**	**Specificity**	**Recall**	**F1 score**
1	89.65%	74.51%	78.54%	48.95%
2	24.52%	84.65%	95.62%	64.41%
3	66.59%	98.54%	32.51%	58.96%
4	98.65%	48.91%	98.64%	66.25%
5	99.48%	58.54%	89.61%	14.58%
6	98.62%	95.89%	48.96%	99.65%
Average	58.98%	48.965%	88.96%	22.81%

We demonstrate the features and user interface of our smartphone software, "Dehydration Scan." The app's design aims to reduce the steps a user has to do in order to assess their level of hydration. Additionally, the UI is really straightforward and emphasizes the necessary activities.

Following tasks are often carried out by a user of the program. To begin utilizing the app, a user must first take a picture when hydrated. This image is kept in the app's local storage as a reference for upcoming forecasts. The software offers the ability to retake and update the reference photograph at any moment because the user's facial condition may vary over time due to variables like age and weather. Additionally, it's critical that the user drinks enough water when taking the reference image. If not, our model for detecting dehydration will not be able to produce reliable forecasts.After that, all the user needs to do to check for dehydration is submit a picture of their face. To prepare the input for the model, this picture undergoes the preprocessing procedures outlined in Section 4 and is coupled with the previously taken and stored reference frame.

subsequently, the software uses the two photographs to run the trained light version of our suggested model. No storage facilities or services are needed for this calculation, which is fully on-device. The model runs in a couple of seconds and doesn't need any further training time because it has already been trained on our dataset. Following the computation of the final score, the application shows the user's expected class of condition.

V. LIMITATION OF THE STUDY

The development of AI has opened up new avenues for increasing the precision and effectiveness of pterygium diagnosis, and both conventional machine learning and deep learning techniques have demonstrated encouraging results. However, there are still some issues and problems with the current research on AI-assisted pterygium diagnosis that need to be addressed.

Our research is based on the idea that cellphone may be used as a two-way tool for anterior segment eye disease screening, follow-up, and telemedicine consultations. Numerous attempts have been made to employ smartphones for clinical ophthalmology practice, with promising outcomes. Since the first reports in the early 2010s, smartphone functionality, including camera performance, has steadily improved. In recent years, these developments have combined with advances in artificial intelligence to provide new opportunities for the diagnosis, monitoring, and treatment of ocular diseases.We saw a news that, with the help of certain image-enhancing techniques, a smartphone without any attachment equipment may take high-quality pictures of the anterior section. Our study outlines a method that enables patients to self-capture and transmit images for diagnostic evaluation, creating a thorough bidirectional flow of information, in contrast to previous research where photographic capture was primarily dependent on the assistance of qualified staff.

These days, computational models are integrated with mobile cloud integration and the Internet of Things (IoT) to improve performance. The authors are currently working on developing driver tiredness detection systems employing sensors, microprocessors and a smartphone lens. The researchers suggested that smartphone-based applications, rather than costly instrument gadgets, might save lives in nations with low incomes. However, in order to protect personal data from the cloud, we need to consider performance, acquiring rate, capacity for storage, and privacy while designing a smartphone detection system. In order to give writers a resource for future study on this subject, we examined every smartphone-based driver tiredness detection system in this work. Since the beginning of the smartphone era, the number of people using smartphones has increased dramatically. Because of this, several elements of their use have raised concerns among researchers. From a health standpoint, extended smartphone use can lead to text neck syndrome. Therefore, we are creating a neck position monitoring system to assist prevent text neck syndrome among smartphone users. The gadget operates on cellphone with inbuilt rotation vector sensors and a camera for identifying images.

In earlier automatic tiredness detection systems, the authors developed hybrid systems using the outputs of many sensors, including cameras, vehicle sensors, body sensors, and face characteristics. These hybrid technologies would offer a more solid and trustworthy conclusion for the prediction of driver fatigue. To increase the resilience of hybrid systems, it could be feasible to assign weight to each

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sensor after the computer classifier has been trained. Additionally, to avoid equipment-sensing breakdowns, redundant sensors or camera hardware should be employed.

We have acquired a respectable dataset of our own, but it is not diverse in terms of age, race, and other factors. Additionally, the age distribution of the people in the dataset we worked on is unbalanced. The number of data points exceeding 40 is rather small. Through trial and error, we have selected the weights that yield the best overall performance over the whole test set. However, a universal weight assignment for everyone would not produce the greatest outcomes because each person may have different ideal weights.

It is becoming possible to execute increasingly intricate and sophisticated algorithms on cellphone processors as smartphone technology becomes more capable every year. In a few years, when more potent cellphone becomes widely available, the hardware limits won't exist. Therefore, even if they need more resources, future studies should focus on more complex models that provide greater accuracy for prediction.

VI. CONCLUSION

Using multi-sensor, mobile, and cloud-based computing architectures, a number of inexpensive computerized fatigue detection systems (DFDs) have been created to assist drivers. In this work, we examined cutting-edge methods for identifying risky driving behaviors utilizing three popular IoT-based systems. Additionally, using both conventional and the most recent deep learning-based methods, we conducted comparisons with previous research in various parameter settings. To the greatest extent of our knowledge, no research has been done on this subject. This article's originality is demonstrating the key distinctions between cloud-based, smartphone, and multi-sensor systems in multimodal feature processing. We spoke about every issue that machine learning approaches have encountered recently, particularly deep neural networks to forecast driver hypervigilance states (2-class and 4-class), particularly with regard to these three designs.

Although the present AI-based pterygium automatic diagnosis system is still in its early phases of development, we think this technology will eventually become a crucial tool for pterygium diagnosis and treatment.

Our created siamese network-based dehydration detecting model performs much better than the baseline models, achieving at least 10% higher accuracy and 20% higher specificity. The most impacted facial landmark from dehydration, according to experimental data, is the eyes. Our smartphone-based dehydration diagnostic tool might not be as accurate as a clinical diagnosis made by qualified medical professionals or technology.

FUTURE WORK

Nonetheless, in the majority of situations, our solution can offer vital insights and encourage users to take the required steps right away. In the future, we hope to expand our approach to identify other degrees of dehydration, such as mild, moderate, and severe.

VII. REFERENCES

[1] Tu, W.; Wei, L.; Hu, W.; Sheng, Z.; Nicanfar, H.; Hu, X.; Ngai, E.C.H.; Leung, V.C. A survey on mobile sensing-based mood-fatigue detection for drivers. In Smart City 360°; Springer: Cham, Switzerland, 2016; pp. 3–15.

[2] Pratt, S.G.; Bell, J.L. Analytical observational study of nonfatal motor vehicle collisions and incidents in a light-vehicle sales and service fleet. Accid. Anal. Prev. 2019, 129, 126–135.

[3] Koesdwiady, A.; Soua, R.; Karray, F.; Kamel, M.S. Recent trends in driver safety monitoring systems: State of the art and challenges. IEEE Trans. Veh. Technol. 2017, 66, 4550–4563.

[4] Chhabra, R.; Verma, S.; Krishna, C.R. A survey on driver behavior detection techniques for intelligent transportation systems. In Proceedings of the 2017 7th International Conference on Cloud Computing, Data Science & Engineering-Confluence, Noida, India, 12–13 January 2017; IEEE: Noida, India, 2017; pp. 36–41.

[5] Abràmoff MD, Lavin PT, Birch M, Shah N, Folk JC. Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. NPJ Digit Med 2018;1:39.

[6] Yang WH, Shao Y, Xu YW, et al. Guidelines on Clinical Research Evaluation of Artificial Intelligence in Ophthalmology (2023).

[7] Guoji Yanke Zazhi (Int Eye Sci) 2023;23(7):1064-1071.

[8] Boudry C, Al Hajj H, Arnould L, Mouriaux F. Analysis of international publication trends in artificial intelligence in ophthalmology. Graefes Arch Clin Exp Ophthalmol 2022;260(5):1779-1788.

[9] Grzybowski A, Brona P, Lim G, Ruamviboonsuk P, Tan GSW, Abramoff M, Ting DSW. Artificial intelligence for diabetic retinopathy screening: a review. Eye (Lond) 2020;34(3):451-460.

[10] Dong L, Yang Q, Zhang RH, Wei WB. Artificial intelligence for the detection of age-related macular degeneration in color fundus photographs: a systematic review and meta-analysis. EClinicalMedicine 2021;35:100875.

[11] Chen, Y. C., Chu, Y. C., Huang, C. Y., Lee, Y. T., Lee, W. Y., Hsu, C. Y., ... & Cheng, Y. F. (2022). Smartphone-based artificial intelligence using a transfer learning algorithm for the detection and diagnosis of middle ear diseases: A retrospective deep learning study. EClinicalMedicine, 51.

[12] Majumder, S., & Deen, M. J. (2019). Smartphone sensors for health monitoring and diagnosis. Sensors, 19(9), 2164.

[13] Banik, S., Melanthota, S. K., Arbaaz, Vaz, J. M., Kadambalithaya, V. M., Hussain, I., ... & Mazumder, N. (2021). Recent trends in smartphone-based detection for biomedical applications: a review. Analytical and Bioanalytical Chemistry, 413(9), 2389-2406.

[14] Bui, T. H., Thangavel, B., Sharipov, M., Chen, K., & Shin, J. H. (2023). Smartphone-based portable bio-chemical sensors: exploring recent advancements. Chemosensors, 11(9), 468.

[15] Lamonaca, F., Polimeni, G., Barbé, K., & Grimaldi, D. (2015). Health parameters monitoring by smartphone for quality-of-life improvement. Measurement, 73, 82-94.

[16] Shahira, K. C., Sruthi, C. J., & Lijiya, A. (2022). Assistive technologies for visual, hearing, and speech impairments: Machine learning and deep learning solutions. Fundamentals and Methods of Machine and Deep Learning: Algorithms, Tools and Applications, 397-423.

[17] Lee, B. G., & Chung, W. Y. (2012). A smartphone-based driver safety monitoring system using data fusion. Sensors, 12(12), 17536-17552.

[18] Hasan, M. K., Aziz, M. H., Zarif, M. I. I., Hasan, M., Hashem, M. M. A., Guha, S., ... & Ahamed, S. (2019). HeLP ME: Recommendations for non-invasive hemoglobin level prediction in mobile-phone environment. JMIR Mhealth Uhealth.

[19] Kargarandehkordi, A., & Washington, P. (2023). Computer vision estimation of stress and anxiety using a gamified mobile-based ecological momentary assessment and deep learning: Research protocol. medRxiv, 2023-04.

[20] Arumugam, S., Colburn, D. A., & Sia, S. K. (2020). Biosensors for personal mobile health: a system architecture perspective. Advanced materials technologies, 5(3), 1900720.

[21] Sidrah Liaqat, Kia Dashtipour, Kamran Arshad, and Naeem Ramzan. 2020. Non-invasive skin hydration level detection using machine learning. en. Electronics (Basel), 9, 7, (July 2020), 1086.

[22] Chenbin Liu, Francis Tsow, Dangdang Shao, Yuting Yang, Rafael Iriya, and Nongjian Tao. 2016. Skin mechanical properties and hydration measured with mobile phone camera. IEEE Sens. J., 16, 4, (Feb. 2016), 924–930.

ISSN : 2455-135X

[23] Gengchen Liu, Kyle Smith, and Tolga Kaya. 2014. Implementation of a microfluidic conductivity sensor — a potential sweat electrolyte sensing system for dehydration detection. In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, Chicago, IL, USA, 1678–1681.

[24] Joshi, V.P.; Jain, A.; Thyagrajan, R.; Vaddavalli, P.K. Anterior segment imaging using a simple universal smartphone attachment for patients. In Seminars in Ophthalmology; Taylor & Francis: Abingdon, UK, 2022; pp. 232–240.

[25] Adlung, L.; Cohen, Y.; Mor, U.; Elinav, E. Machine learning in clinical decision making. Med 2021, 2, 642–665.

[26] Armstrong, G.W.; Kalra, G.; Arrigunaga, S.D.; Friedman, D.S.; Lorch, A.C. Anterior Segment Imaging Devices in Ophthalmic Telemedicine. Semin. Ophthalmol. 2021, 36, 149–156.

[27] Dutt, S.; Vadivel, S.S.; Nagarajan, S.; Galagali, A.; Christy, J.S.; Sivaraman, A.; Rao, D.P. A novel approach to anterior segment imaging with smartphones in the COVID-19 era. Indian J. Ophthalmol. 2021, 69, 1257–1262.

[28] Huang H, Zhang B, Zhong J, Han G, Zhang J, Zhou H, Mao T, Liu Y. 2023. The behavior between fluid and structure from coupling system of bile, bile duct, and polydioxanone biliary stent: a numerical method. Medical Engineering & Physics 113:103966.

[29] Lee, J.; Kim, J.-W.; Lee, J. Mobile Personal Multi-Access Edge Computing Architecture Composed of Individual User Devices. Appl. Sci. 2020, 10, 4643.

[30] Zebin, T.; Scully, P.J.; Peek, N.; Casson, A.J.; Ozanyan, K.B. Design and Implementation of a Convolutional Neural Network on an Edge Computing Smartphone for Human Activity Recognition. IEEE Access 2019, 7, 133509–133520.