Use of telemedicine and artificial intelligence in Eye and ENT: a boon for developing countries

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***Abstract*— Developing countries like Nepal face challenges in accessing health services due to sparse distribution in communities, difficult geographic terrain, limited transportation, poverty, and lack of health human expertise in rural areas. The COVID-19 pandemic added woes to the wound. To address this gap, the Hospital for Children, Eye, ENT, and Rehabilitation Services adopted an innovative approach to remote rural patient care using telehealth and artificial intelligence in close coordination with IT professionals and healthcare professionals. We developed a deep learning-based disease prediction model that incorporates telemedicine with AI for screening and diagnosing Eye and ENT diseases using non-specialist health workers. Deep learning-based disease prediction models in Diabetic Retinopathy (DR) and Glaucoma added quality specialized services to telehealth. This paper presents the adoption of digital innovations and the incorporation of telehealth to tackle various diseases. To predict DR, 61,458 colorful retinal photographs from fundus photography and 1500 for Glaucoma were used. To reduce the biases, EyePACS data sets were also incorporated. Inception V3 transfer learning model was used for DR and employed DenseNet architecture for Glaucoma. An accuracy of more than 90 %in both models was achieved. Accurate specialized diagnosis, better medical care, patient monitoring, limited specialized hospital visits, and easier with shorter wait times are now possible. In the future, this successful model can be replicated nationally and in other developing countries.**

Keywords—Telemedicine, Artificial intelligence, Deep Learning, Diabetic Retinopathy screening, Glaucoma screening.

I. Introduction

The use of digital technology has made significant contributions to the fight against the COVID-19 pandemic in the global context and reaching the unreached in treating health issues in local developing countries context. It has impacted and transformed many sectors including health. It has revealed many viable solutions in health such as remote patient screening, specialized treatment, condition tracking, resource prioritization, and focused response design [21]. Many of the above-mentioned activities are now available because of the usage of telemedicine and artificial intelligence (AI). These advancements may also be able to address several urgent daily needs of communities and challenges that come during COVID and beyond [1].

This paper shares the experiences of developing and using a telemedicine system augmented by an AI prediction model deploying non-specialists for developing countries. Here, we also discuss its potential for future expanding its application in clinical areas as well as its applicability for both rural and urban areas of Nepal and other countries on similar development trajectories. Besides, the lesson learned, challenges, and shortcomings in implementing the system will be probed.

II. B. P. Eye Foundation's telemedicine and AI System

When COVID-19 was on the rise in late 2020, the B.P. Eye Foundation (BPEF) initiated telemedicine services in three centers to reach out to the poor to deliver healthcare services at their doorstep. This was expanded to five centers in early 2021. The system was operated at remote centers by locally available community medicine assistants (CMA) who were trained for three months at the center by BPEF in Eye, ENT, and IT departments and then returned to their communities with the necessary telehealth hardware (Desktop, printer, Internet, Digital Otoscope, fundus camera, refractometer, and tonometer) and telehealth and audiological app software. This Community Ear Health Worker (CEHW) communicates with experts stationed at the base hospital using both synchronous and non-synchronous means daily.

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A. Telemedicine

Telemedicine is being used by health professionals in the transfer of data, communication, and providing clinical and educational services, communication, and providing clinical and education services. It also is used effectively in situations where there is limited availability of health human resources [21]. Patients in distant poor communities with limited healthcare facilities are connected, thus, minimizing travel time and providing access to expert care at the doorstep [8] [9]. Increased capacity and availability of healthcare through telehealth for both chronic and acute diseases minimize wait times while obtaining prompt expert consultation.

Furthermore, because of the COVID-19 pandemic risk, individuals avoid going to the hospital unless it is an emergency. As a result, diseases pile up. Telemedicine available remotely can help benefit such patients [2].

In terms of implementation, various projects in developed countries have been implemented in the last 10–15 years [10][11][12]. Some other initiatives with an additional feature, such as those in Western Australia, have focused themselves on including medical education. According to the poll, roughly 73 percent of responding healthcare facilities in Western Australia employ telemedicine, with facilities located further out from Perth using more telehealth services [13].

Telemedicine systems however were not widely used in poor countries. It could be either because of high cost, technological anxiety, resistance to technology, social influence, lack of necessary infrastructure and trust, and convenience of usage. However, during the COVID pandemic, a great deal of technological progress surfaced. Various digital health solutions were applied during the pandemic and have proven their potential in developing countries[14][15]. A market Survey was undertaken by Mamoun et al in the year 2020 to examine the degree of acceptability of online health platforms by the general public in developing nations. The results of the survey showed that 92.55 percent of those polled accept and trust internet applications for healthcare delivery [16].

Considering these results and researching various telemedicine models CHEERS developed and implemented a suitable telemedicine system. The software is placed securely on a local server. To allow for proper medical management, the results are conveyed to the patient and healthcare provider promptly. Although a physician appointment needs to be entered into the system manually, most routine outcomes can be communicated in an automated manner. With an inbuilt video consultations facility incorporated in the software, it reduces patient travel and clinic visits while improving telemedicine consultation quality.

Telehealth service is performed either synchronously using real-time interaction, or asynchronously using a store-and-forward way. After experiencing the telemedicine system for a few months, we discovered that telemedicine alone could not solve the remote treatment of specific specialist diseases including DR and glaucoma while providing remote service delivery. As a result, we built an AI prediction model for DR and Glaucoma to improve the quality of service.

The report published in June 2021 by WHO mentions that AI is useful for developing countries and poor rural communities with limited access to healthcare in availing access, [17].

B. Use of non-specialist health workers

In Developing countries like Nepal, there is a severe lack of specialized health human resources. Those few existents too are stationed in metropolitan cities due to the non-availability of infrastructure and non-lucrativeness at the periphery. As a result, there is an ever-increasing ratio between disease prevalence and treating clinicians. There is thus an immense need for grassroots health workers who can provide the basics of management and contribute to reducing the health burden of a country. Nepal to bridge the burden has introduced CMA. CMA is a Government accredited program that trains class ten pass students for 18 months to produce competent community health workers who provide preventive, promotive, curative, and rehabilitation services as well as provides primary health care services at the community level.

C. Artificial Intelligence

AI as we know is an intricate technology having multiple constituents; advanced algorithms, machine learning (ML), and Deep Learning (DL).

AI in recent years has made notable transformations in medical imaging, with multiple approved (USA) deep-learning algorithms and measuring applications. Many imaging providers think AI will enhance diagnostic imaging over the next decade [3]. AI applications are used today extensively in diagnosing, laboratories, treatment, robotic surgeries, safety, scientific research, games, and many more.

In medical diagnosis, Ophthalmology has been a leader among all medical specialties in applying AI in clinical practice. As mentioned earlier, the first fully automated AI for the Diagnosis of diabetic retinopathy was the first to receive FDA approval for any medical diagnosis in the world. In recent days, AI, ML, and DL are deployed in the ophthalmic field to substantiate disease diagnosis, corneal topography, calculating intraocular lenses, diabetic retinopathy (DR), age-related macular degeneration (AMD), glaucoma, and recently for Retinopathy of prematurity (ROP), and various diseases of the cornea [4].

Despite wide application across different areas of eye care and ear care, AI still lags in clinical use in health in Nepal. Given, Nepal's geographic diversity, difficulties of access, cost of care, and shortage of human resources, the application of AI, together with another digital technology-telehealth can help solve problems of poor communication and delayed diagnosis and intervention.

III. CHEERS AI MODEL

BPEF has introduced its disease prediction model in DR and Glaucoma utilizing Artificial Intelligence (AI), keeping in mind the scarcity of trained specialists in Nepal. These AI models were developed with the help of local IT specialists with AI backgrounds. They are web-based applications that CMA can access through an internet connection at the community level. The CMAs who have been trained by BPEF use a fundus camera to collect photos that are then fed into the disease prediction model. CMAs treat patients directly or consult with specialists stationed at Center Hospital based on the prediction (BPEF). BPEF has introduced its illness prediction model in Diabetic Retinopathy and Glaucoma utilizing AI, keeping in mind the scarcity of trained specialists in Nepal

A. *Model Architecture*

In this study, a deep-learning (DL) model can predict patients with the risk of diabetic retinopathy and glaucoma. The input to the model was the color fundus images. Color fundus images, which are commonly used to assess the stage of diabetic retinopathy, show signs of retinal microvascular alterations induced by diabetes. The approach applied is based on the Inception-v3 architecture. The architecture works by combining numerous convolution filter inputs into a single input. At the same time, it performs pooling. Thereafter, all the results are concatenated. This allows the model to extract many levels of features from each input.

Whereas for Glaucoma prediction we used DenseNet. DenseNet (Dense Convolutional Network) emphasizes deep learning networks in-depth, crafting them more effectively to train by using shorter connections between layers.

In addition to fundamental convolutional and pooling layers, DenseNet has extra components; Dense Blocks and Transition Layers.

B. *Study population and data sets*

The data set used were fundus images of the human retina from CHEERS and EyePACS. EyePACS datasets were downloaded from Kaggle [18]. 7:3 training and testing ratio were followed. CHEERS data set were labeled by all 3 of its retinal surgeons, independently.

C. *Preprocessing*

During this phase, Image enhancement, cropping, and resizing were done. The following steps were taken.

1. A large dataset from EyePACS from Kaggle was taken. Additionally, data sets from CHEERS were also mixed to customize to the local context.
2. The photographs were first cropped to eliminate the neutral backdrop and scaled to 500 x 500 pixels. Four alternative preprocessing images were experimented with to see which was the best input for the Convolution Neural Network (CNN). There on, both the circled and square images were resized to preserve consistency among the images. This is because the fundus images used were obtained by a variety of fundus cameras manufactured by different companies.
3. The retinal image is generally created under various lighting situations and has a wide range of brightness and contrast. Different techniques of picture acquisition, as well as the existence of diseases, make it difficult to develop reliable image segmentation. Thus, before sending the photos into the model, image enhancement algorithms were applied to improve their clarity. A two-step preprocessing procedure was employed.
4. The contrast limited Adaptive histogram equilibrium (CLAHE) technique to raise the contrast of the local regions to make local details more visible.
5. Subtracting the image's local average color. This helps the area of interest protrude sharply from the background and provided a better quality image.

D. *Data Augmentation*

Data augmentation was used to balance the training set and expand the number of photos for training by rotating from 0 to 360 degrees, zooming in and out from 0 to 20 pixels, and flipping horizontally and vertically. This augmentation was done at random for all photos in the training set, and images were replayed with varied augmentation parameters for classes 1, 2, 3, and 4. The resulting final balanced data sets consisted of 61,458 images.

E. *Model Training*

DL model was chosen as it is a discipline of machine learning that entails hierarchical layers of nonlinear processing stages for learning unsupervised features and classifying patterns [5]. DL has been employed in a wide range of medical image analysis applications. Even when a large amount of heterogeneous data is combined, it may learn the features of the input data. Of several DL methods available, we chose the CNN architecture over the others because it has been proven to be more effective and widely used [6]. The CNN architecture is made up of three levels. Convolution (CONV), pooling, and fully connected (FC) layers. CONV layer uses different filters to extract features. The FC layer has a compact feature that is utilized to describe the entire image while pooling layers are used to lower the dimension of the feature maps. On the ImageNet data set, there are different pre-trained CNN architectures available. They are also named transfer learning. The cause for employing transfer learning in our situation is that image categorization models include millions of parameters, a lot of labeled training data, and computer resources to train them from scratch. Transfer learning hastens up the process by utilizing a block of a model that has already been trained on a related chore in a new model.

In this research, various transfer learning models - ResNet, AlexNet, VGG, denseness, inception V3, and EfficientNet were applied. Among them, Inception V3 was the most promising for Diabetic Retinopathy and DenseNet for Glaucoma. We also utilized Perform Exploratory Data Analysis on Inference to figure out which photographs were causing problems -out-of-focus images and too bright, and too dark images. A new dataset was produced based on the observation, with the undesired data removed. After, testing multiple models we discovered that Inception V3 for DR generated the most promising result.

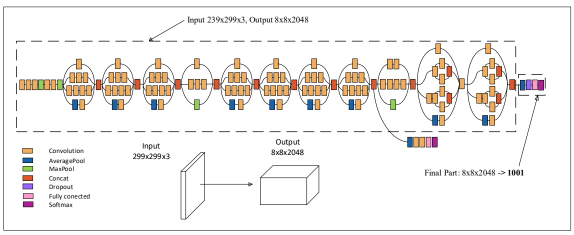

Fig 1. A high-level diagram of the Inception V3 transfer learning model (Source: https://cloud.google.com/tpu/docs/inception-v3-advanced)

F. *Results: Performance Measures*

In this study, various performance measuring indicators and matrices such as accuracy, sensitivity, specificity, and area under the curve computation was used. We achieved a sensitivity of 98.57%, a Specificity of 92 .97%, and an Area Under the Curve (AUC) was 0.988. The Clinical Utility (+ve) is found excellent (0.9154) [7]. Table 1 and 2 shows the details of the performance measures.

TABLE 1: PERFORMANCE MEASURES FOR DIABETIC RETINOPATHY

Statistics	Value
Sensitivity	98.57%
Specificity	92.97%
Accuracy	93.82%
Clinical utility +	0.9154

TABLE 2: PERFORMANCE MEASURES FOR GLAUCOMA

Statistics	Value
Sensitivity	92.74%
Specificity	96.49%
Accuracy	96.28%
Clinical utility +	0.849

The built model was deployed on an Ubuntu server using Flask. Apart from running the model, the flask application programming interface (API) is also used for authentication and saving the tested photos.

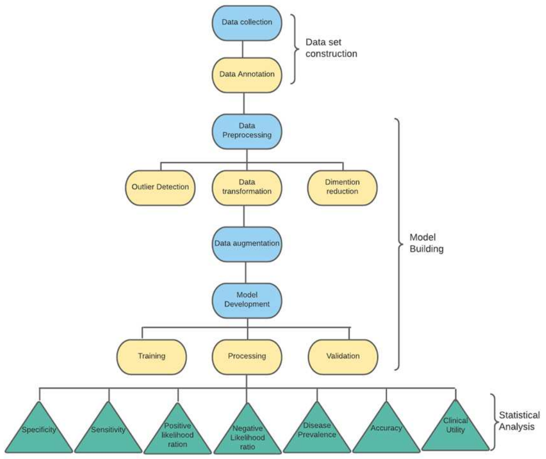

Fig 2. Model development Methodology Framework

To show the overall process structure mentioned above, the model development methodology framework is depicted in Figure 2, which is separated into three sections. Data set construction, model development, and statistical analysis. Data collection and annotation are both parts of the dataset development process. Model development includes dimensional reduction, data translation, outlier detection, augmentation, and model creation. Finally, a statistical analysis was performed to evaluate the model's performance.

IV. DISCUSSIONS

Telemedicine through practice for a long has gained momentum during COVID-19 and has emerged as a boon in countries that lack healthy human resources [22]. People and places having difficult geographic terrain, inaccessible road, minimal or non-existent health facilities, lack of transportation, and lack of mobility either due to age, gender, poverty, or disability are most beneficial.

Today use of both software and hardware has progressed rapidly. User-friendly software with quality image transmission and communication has lessened the time spent by experts based at the center. It has also reduced the need for specialists to be placed physically at the periphery. The availability of arrays of portable digital equipment makes it accessible and cost-effective [23]. There is a huge scope of data storage and analysis for asynchronous use. Advancement in telehealth technology has been shown to directly impact patients' perspectives on quality service as they are being screened by non-specialists (CMA) [24]. As specialized services are required, patients can speak directly with the hub hospital via video consultation from peripheral centers. This would otherwise be difficult, time-consuming, and costly. Nowadays awareness of telehealth is growing, and there is a tremendous rush of patients to peripheral telehealth centers for consultation and management. This indicates that expansion to places where health human resources are scarce would act as a catalyst in reducing the disease burden and overcrowding of tertiary centers [25].

Telehealth has many potential benefits and many challenges. In developing countries, mainly effective technological training for all system users and better infrastructure setup and operation has been identified as major challenges. Furthermore, specialized treatment is also a barrier, but it can be mitigated by utilizing AI-based prediction models [26].

The use of AI in developing prediction models for diagnosing DR and Glaucoma is not new [27]. Much blindness has been averted through early diagnosis and treatment. Many have used AI models with varied sensitivity and specificity. In our context, the use of the DR model with a sensitivity of 98.57% and specificity of 92.97% and similarly Glaucoma prediction model with a sensitivity of 92.74% And specificity of 96.49% through the use of telemedicine has proven to be a very effective and potential tool for reaching out to the unreached through the utilization of minimally trained non-specialist.

Non-specialists have been utilized to bridge the gap between disease burden and available human resources in a variety of situations. At CHEERS, the use of non-specialist (CMA) with minimal training in telehealth and AI models have shown good result. Training in the intricate use and handling of digital equipment, and software, and imparting basic knowledge in Eye and ENT disease and treatment is essential. This is rewarding, even though it appears to be tedious at first. Many diseases and disabilities can be avoided and treated, and those who require early rehabilitation are provided with it.

With every new effort, there are always advantages, lessons to be learned, and shortcomings. Below, we share our telehealth and AI model experience with the use of non-specialists.

A. *Benefits*

The impact of these services is direct for reaching out to the unreached. With increased coverage of healthcare delivery, community health awareness, and healthcare local health workers are better employed, and clinical specialists are less burdened since they can execute quality work. Experts are either not necessary or only required every month for further management in the field (not needed for basic screening work). Furthermore, local patients acquire faith in healthcare due to direct engagement with professionals at the center. Early disease detection and intervention can assist to prevent morbidity and disability. At a low cost, specialized healthcare can be delivered to your doorstep. The AI disease prediction models are used to provide a quality diagnoses by non-specialists. It's easy to follow up. In the peripheral, high-performing digital portable equipment is accessible at a reasonable price.

B. Lessons learned

The following are some of the lessons learned by putting these services in place. Because screening and diagnosis alone are insufficient, basic medication must be readily available. Where the internet is slow or non-existent, a data card is required. Clinical staff initially resisted adopting new technologies and techniques. The use of digital equipment necessitates extensive training. Additionally, dedicated telehealth staff is required at the hub hospital. At least two staff members at every telehealth center must be trained to avoid service interruptions. It is beneficial to have a focal person at each local community center. Dealing with the next steps in the management of detected cases that have not been referred. As a result, they rely on CHEERS for additional assistance as much as feasible. The AI-induced prediction model is very effective and needed to predict other disabling causes. Better community sensitization in healthcare was achieved.

C. Shortcomings

Although there is a lot of demand, we cannot meet the demand made by other remote communities on Telehealth & Artificial Intelligence due to financial constraints. Besides, due to poor Internet service hinders smooth service. Data card needs to be kept handy all the time._Additionally, there is limited availability of various digital equipment and prediction models making some of the disease diagnoses difficult. The electric blackout-out problem is a hindrance to telehealth. Portable generators or solar backup availability would be an added advantage. Furthermore, we encountered a problem of early adoption and sustainability in some locations, which was overcome by continuous training and follow-up.

V. Conclusion

Through this paper, we would like to express that telemedicine and AI be successful in mitigating the burden of disease in developing nations such as Nepal since AI adds extra capabilities to the telemedicine system. The major focus should be on proper planning, development, infrastructure setup, training, continuous technological support, monitoring, and control. One of our significant limitations was that we could not fully utilize technology while taking into account the user's perspective and IT competence.

In the future, the need for smarter and better healthcare will rise exponentially. We need the help of telemedicine to improve and implement current healthcare solutions in different areas as medical specialists continue to make discoveries in the field of medicine. Naturally, this will reduce the burden on specialists on routine work and they can focus more on specialized diseases. Hospitals and medical institutes will be able to provide healthcare 24 hours a day, seven days a week if the world including developing countries embraces telemedicine with AI technology.

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