A Novel Web Application Framework for Ubiquitous Classification of Fatty Liver Using Ultrasound Images

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***Abstract*—Medical imaging techniques are being profoundly used for diagnosis of many diseases. In many of the remote areas in the developing nations, patients who live in rural areas are facing vital health disparities compared to the general population. In such scenarios, eHealth can offer promising solutions. The eHealth especially aims at developing digital applications for offering high accuracy diagnosis even in remote areas. Also, the integration of eHealth with advanced technologies such as deep learning and artificial intelligence will further improve the diagnostic accuracy and also reduces the duration. In this paper, we develop a novel low-cost and easily scalable eHealth architecture comprising of a web application which enables clinicians in fatty liver classification using ultrasound images. The developed web application framework uses a deep learning model (using CNN) for accurate classification of fatty liver using ultrasound images. The clinician in a remote location with a moderate internet connectivity can upload the scanned ultrasound image to the developed web application and the application identifies if any abnormality is present. From the performance analysis, it is observed that the developed model achieves an accuracy of 91.37%. Also, regarding latency the developed classification model predicts the abnormality presence in less than 20 ms. However, including the network latency, it is observed that the developed eHealth architecture predicts with a latency of less than 150 ms using moderate network connectivity.**

***Index Terms*—eHealth, Artificial Intelligence, Fatty liver classification, Ultrasound, CAD, IoT Architecture**

I. Introduction

The Internet of Things (IoT) is rapidly proliferating into many sectors including healthcare. Today most of the healthcare services starting from in-hospital patient care to remote healthcare are utilizing IoT technologies to improve the affordability and reachability [1]. Especially in the developing countries where healthcare providers are inadequate compared to the total population, this can be a promising solution [2]. In the recent past many technologies such as wearables for automated electrocardiogram monitoring, glucose and blood pressure monitoring, and epilepsy detection have been developed at low cost using IoT technologies [3], [4]. However, there is a long way to go before the healthcare becomes truly pervasive and ubiquitous, especially in the developing nations. Importantly, in the case of medical imaging technologies, the high cost of the infrastructure is hindering the adoption of IoT technologies which realizes the telemedicine or remote healthcare delivery [5]. Due to the lack of skilled sonographers or physicians in the rural areas, the majority of people are suffering from inaccurate diagnosis being offered by the semi-skilled clinicians. Especially, the ultrasound imaging which is a widely used modality for diagnosing various diseases pertaining to multiple organs requires skilled clinicians for offering accurate diagnosis [6]. Hence, we strongly feel that the usage of IoT and artificial intelligence based technologies will significantly improve the current state of the healthcare. In this paper, our primary contributions include:

1) Developed a novel low-cost and scalable eHealth architecture for classifying the fatty liver using ultrasound images.
2) Developed a web application that enables sonographers in the remote areas for classifying the fatty liver by uploading the scanned ultrasound images.
3) The web application developed using a convolutional neural network (CNN) along with fine-tuning and transfer learning based framework for the classification of the fatty liver using ultrasound images.
4) Development of dataset comprising of 58 liver ultrasound images (of which 22 correspond to fatty liver) for analyzing the performance of the proposed eHealth framework.
5) Performance analysis considering latency and classification accuracy as the key performance metrics.

The usage of information and communication technology (ICT) or more broadly IoT technologies in healthcare delivery is generally referred to as eHealth [7]. In promoting universal health coverage, eHealth plays an important role by providing low cost healthcare services to remote and under-served populations. It improves the accuracy of diagnosis by utilizing IoT and artificial intelligence technologies. Ultrasound scanners are usually located in well-established hospitals due to their huge form factor, cost and need for a person who is well trained in sonography. With the advancements in computing technology, conventional ultrasound scanner are reduced to portable ultrasound scanners for improving the ease of scanning in rural and emergency locations [8], [9]. Also, they support IoT technologies wherein a doctor situated

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in a different location can administer the scanning in real-time. However, many hospitals located in both urban and rural areas still use the traditional ultrasound scanners which do not support remote administration due to multiple factors such as lack of investment [10], [11].

Authors in [12] developed a low-cost portable system to perform obstetric ultrasonography to monitor baby in the womb using an eHealth architecture. However, this requires the conventional ultrasound scanner to be replaced with the developed portable ultrasound sound scanner. Authors in [13] developed a multimedia framework to support eHealth applications using scalable video coding (SVC) extension for MPEC-4 AVC/H.264 which enables a doctor in a different location to administer the scanning in real-time. This solution is feasible in areas where high bandwidth network connectivity is available and may not be a suitable solution for rural areas. In [14] In [14], authors proposed an abnormality detection based on Viola Jones and Support Vector Machine (SVM) classifier to detect the abnormality in ultrasound image. In [15], authors proposed a framework for compressing the ultrasound images using web real-time communication (WebRTC) framework technology for low data real-time eHealth applications. However, it still requires the high performance network connectivity which is not available in rural areas. Also, in [16] the authors have developed similar frameworks for tele-diagnosis wherein the ultrasound scanning information is streamed to the expert side for getting inferences. In all the above studies the major drawbacks include the following: (1) the infrastructure needs to be replaced, (2) requirement of high performance network connectivity and (3) manual observance of the ultrasound data which is prone to errors and entirely depends on the skill of the sonographers. Hence, in this paper, we developed a web based architecture wherein a clinician can upload the ultrasound image and can get accurate diagnosis information. This architecture does not require any change in the existing infrastructure and is an easily scalable solution especially for developing nations.

The rest of this paper is organized as follows. Section II describes the proposed architecture and the functional units present. Section III describes the developed CNN based classification framework for accurate classification of fatty liver using ultrasound images. In Section IV, we discuss the dataset developed for analyzing the performance of the proposed architecture and the key insights observed from the performance analysis. Finally, Section V concludes the paper by summarizing the work performed and discussed the future scope of this work.

II. Proposed Novel eHealth Architecture for Accurate Web Based Fatty Liver Classification

Fig. 1 shows the ultrasound images of liver under normal conditions and those with affected by fatty liver. Excess fat accumulated in the liver can lead to fatty liver conditions and can cause severe liver damage. The normal liver usually contains 5 to 10% of the fat and if the fat concentration exceeds beyond this limit, it is observed as a fatty liver condition. The liver in general is capable of repairing if the old cells are damaged by rebuilding the new liver cells until repeated liver damage occurs. Currently, the fatty liver disease is becoming a more prevailing condition, affecting about 25 to 30 % of the population in both the developed and developing countries [17]. If the condition is left untreated, fatty liver leads to more harmful steatohepatitis gradually leading into liver cancer. Early detection of fatty liver can thus prevent from the permanent failure of the liver. To identify the fatty liver condition, ultrasound imaging is the widely used diagnostic method.

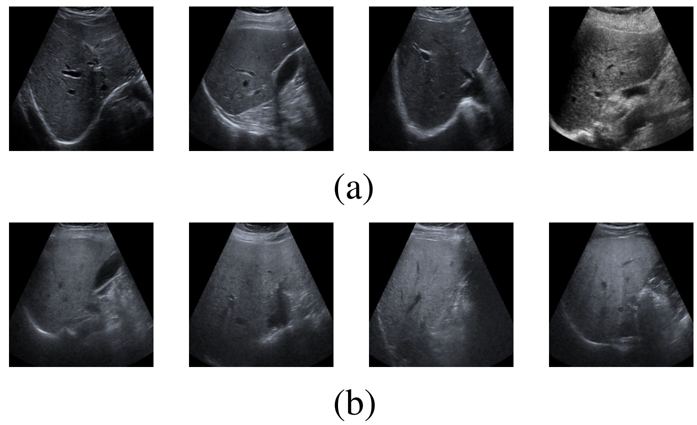

Fig. 1. (a) Ultrasound images of liver under normal conditions, (b) Ultrasound images of liver under fatty liver conditions.

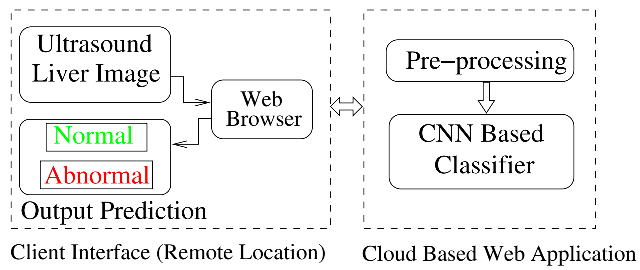

Fig. 2. Proposed novel low-cost and scalable eHealth architecture for accurate web based fatty liver classification

Fig. 2 shows the proposed architecture for the novel low-cost and scalable eHealth architecture for fatty liver classification. The entire architecture can be broadly classified into two functional units and are described in the following subsections.

A. Client interface (remote location)

The client who is a semi-skilled clinician is the person who performs the ultrasound scanning to the patient. Once the ultrasound scanning is performed, the client uploads the ultrasound images generated into the web based interface provided. Upon successful upload, the image will be classified regarding whether it is normal or abnormal using the web application present in the cloud. Thus classified information will then be sent back to the client.

B. Cloud based web application architecture for fatty liver classification using ultrasound images

In the cloud, we have developed a web application which uses the ultrasound image uploaded by the client for the detection of the fatty liver conditions. The developed framework comprises of a convolution neural network (CNN) based trained model for the classification and the developed CNN based model along with the popular Flask framework is used for the development of the web application. Flask is a light-weight backend framework developed to serve the usage of pre-trained models over the internet connectivity and importantly, it runs on python [18]. The finer details of the developed CNN based model will be provided in the Section III.

The major advantages of the proposed eHealth framework includes:

- The developed framework is diagnostic of the ultrasound machine present in the clinical centers.
- Avoids the need for costly and updated ultrasound machines and works with the existing infrastructures.
- The service is available ubiquitously and can be used with moderate network bandwidth.
- It can be easily scaled depending on the requirements.

Fig. 3 and 4 shows the developed web interface for the client to upload the scanned ultrasound image along with the classified output. The client first uploads the image and then upon submitting the request the web application classifies the image into either normal or abnormal and displays it to the client or clinician.

Fig. 3. Developed web interface along with the ultrasound and prediction when tested using a normal liver image.

Fig. 4. Developed web interface along with the ultrasound and prediction when tested using a liver image with a fatty liver condition.

III. Developed CNN based accurate fatty liver classification framework

In [19], we have developed a novel CNN based accurate fatty liver classification model using ultrasound images. The same model is adopted in this paper for the classification of fatty liver using ultrasound images. The architecture comprises of a pre-trained VGG-16 model along with the transfer learning and fine-tuning. VGGNet using CNN is initially designed with different layer depths aiming for image recognition tasks. Preliminary analysis of VGGNet offered a promising accuracy of 92.7% when validated using the ImagNet dataset comprising of 14 million images from 1000 classes [20]. In this paper, we make use the 16 layers VGG-16 with convolution blocks(including convolution layers and max-pooling layers) and a fully connected classifier. The fine-tuning is carried out using the pre-trained VGG-16 model in Keras. Traditionally, the convolution 2D layers in VGG-16 consists of 512 nodes for convolution layers, however, in our experiment we fine-tuned the network from using 512 nodes to 256 nodes. Also, we fine-tuned fully connected layers having 4096 nodes to 256 nodes, and the output layer comprises two neurons whose output corresponds to the two classes (normal and abnormal) in this study. During the training of the model, the weight parameters of the output layer are initialized using random Gaussian distribution, and the training is performed over 100 epochs. Since the development of the CNN based accurate fatty liver classification framework is not our primary contribution in this paper, we would like to advise the readers to kindly refer [19] for more details on the developed model. However, we would like to highlight that the database used for validation in [19] is different from what we used here.

IV. Results

The publicly available datasets for ultrasound images of the liver are very few. Hence, due to the unavailability of the public datasets, we acquired and developed our own dataset using a GE LOGIQ F6 ultrasound scanner in collaboration with MNR Medical College, Sangareddy, Hyderabad, India. The dataset consisted of 58 representative liver images comprising of both fatty liver (22 images) and normal conditions (36 images). We cropped the images which does not convey any diagnostic information such as hospital name, time of the diagnosis, etc. Also, since the pre-trained models are trained with an input image size of 224×224 pixels, the images of our dataset were also resized to 224×224 pixels for compatibility. The performance of the proposed model is analyzed considering classification accuracy, confusion matrix, F_{score}, $Precision$, and $Recall$ as the key performance metrics. The description of the considered performance metrics are given below:

$$F_{score} = 2\frac{recall*precision}{(recall+precision)}, \quad (1)$$

$$Recall = \frac{N(TP)}{N(TP)+N(FN)}, \quad (2)$$

$$Precision = \frac{N(TP)}{N(TP)+N(FP)}, \quad (3)$$

TABLE I
CONFUSION MATRIX OF THE PROPOSED ALGORITHM

True class	Predicted class	
	Normal	Abnormal
Normal (36)	33	3
Abnormal (22)	2	20

TABLE II
PERFORMANCE ANALYSIS OF THE PROPOSED ALGORITHM FOR DETECTION AND CLASSIFICATION OF FATTY LIVER.

Class	Precision	Recall	$F1_{score}$	Support
Normal	94.2	91.6	92.8	36
Abnormal	86.9	90.9	88.8	22
Avg/total	90.5	91.2	90.8	58

$$Accuracy = \frac{N(TP) + N(TN)}{N(TP) + N(TN) + N(FP) + N(FN)}, \quad (4)$$

where $N(TP)$ indicates the total true positives, $N(FP)$ indicates total false positives, $N(TN)$ indicates total true negatives and $N(FN)$ indicates the false negatives. All these measures are computed for each class, and an overall measure of the algorithm is computed by taking the average of all these measures across the two classes. Also, we have analyzed the latency for classification to understand the suitability of the framework in areas where moderate internet connection is available. From the analysis it is observed that the developed fatty liver classification framework achieved an average classification accuracy of 91.37%. Out of the 22 images representing fatty liver, 20 are classified correctly while the other 2 images are classified as normal. Similarly, 3 of the 36 normal images are classified to be abnormal. Table IV shows the confusion matrix obtained when the developed framework is validated using the developed dataset. One can observe that the developed algorithm achieves a classification accuracy of 91.37%. Table II gives the obtained F_{score}, $Precision$, and $Recall$. The highest precision of 94.2% is achieved for Normal category followed by 86.9% for Abnormal. On an average, the proposed algorithm offers a precision of 90.5%. Regarding recall, the highest is achieved for Normal class with 91.6%; the lowest recall is obtained with Abnormal 90.9% and the average recall obtained is 91.2%. Finally, the average F_{score} is observed to be 90.8%, where maximum is Normal 92.8% and minimum for Abnormal 88.8% respectively.

Also, it is observed that the developed classification model offers a latency of 20 ms for an image to be classified when running on an Intel i7 processor with 16 GB RAM. However, it is observed that in most of the cases, the latency does not exceed 150 ms with moderate network connectivity (approximately 2 Mbps bandwidth). We strongly feel that this paper can aid future researchers for improving the state of the art research in the development of scalable and low-cost eHealth applications.

V. CONCLUSION

In this paper, we proposed and developed a low-cost and easily scalable eHealth architecture comprising of a web application for automatic classification of fatty liver using ultrasound images. The developed web application is easy to use and requires no change in the current infrastructure. The ultrasound images obtained using the traditional ultrasound scanners can be uploaded to the developed web application using moderate network connectivity and the web application then classifies the image into either normal or abnormal using a CNN based framework. The performance of the proposed framework is tested with with 58 ultrasound images, we have developed a custom database comprising of 58 ultrasound images with liver information of which 36 correspond to liver images are normal conditions and the rest correspond to a fatty liver condition. It is observed that the proposed framework achieves an average accuracy of 91.37%. Also, the latency analysis shows that the proposed CNN model predicts within 20 ms when running on a PC with Intel i7 processor and 16 GB RAM. Also when considered along with the network latency the total latency observed is approximately 150 ms when used with moderate network connectivity. Hence, we strongly feel that the proposed eHealth framework will help future research in developing low-cost, easily scalable and ubiquitous eHealth frameworks. Our future scope of this work is to develop a more robust classification framework which can eliminate the false negatives. Also, we would like to consider real-time trials in coordination with hospitals to analyze the performance in real constraints.

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