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SignQuiz: A Quiz Based Tool for Learning Fingerspelled Signs in Indian Sign Language Using ASLR

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ABSTRACT Sign Language is one of the media of communication for deaf people. One should learn sign language to interact with them. Learning usually takes place in peer groups. There exist very few study materials for sign learning. Because of this, the process of learning sign language learning is a difficult task. Fingerspelled sign learning is the initial stage of sign learning and moreover, are used when no corresponding sign exists or signer is not aware of it. Most of the existing tools for sign language learning use external sensors which are costly. This paper discusses SignQuiz, which is a cost-effective web-based fingerspelled sign learning application for Indian sign language (ISL) utilizing automatic sign language recognition technique. SignQuiz helps to learn signs without any external help. This is the first attempt in ISL for learning finger spelled signs using a deep neural network. The results indicate that SignQuiz is better than the printed medium for fingerspelled sign learning.

INDEX TERMS Assistive technology, sign language, learning technology.

I. INTRODUCTION

There are around 466 million people worldwide with hearing loss and 34 million of these are children. 'Deaf' people have very little or no hearing ability. They use sign language for communication. People use different sign languages in different parts of the world. Compared to spoken languages they are very less in number [1], [2]. India has its own sign language by the name Indian Sign Language (ISL). In developing countries there are only very few schools for deaf students. Unemployment rate among adults with hearing loss are very high in developing countries [3]. Data from Ethnologue [4] states that among deaf population in India, which is about 1% of total population, literacy rate and number of children attending school is very less. World Health Organization (WHO) "factsheet" states that teaching sign language will benefit children with hearing loss. It goes on to state that official recognition of sign languages, increasing the availability of interpreters and providing transcription in sign languages greatly improve accessibility.

Signs in sign languages are the equivalent of words in spoken languages. Signed languages appear to favor simultaneous sign internal modification [5], rather than the concatenation of morphemes. Although sign languages are rooted in manual gestures, they are not iconic in nature [6]. But learners in the initial stages of SL learning use iconicity as a mnemonic aid to remember new signs. But the lack of iconicity makes it difficult to learn new signs for those who learn SL as a new language.

Fingerspelling is the representation of the letters of a writing system and sometimes numeral systems. It acts as a bridge between sign language and oral language. Indian Sign Language (ISL) can represent English alphabets A-Z using finger spelling. It can be one handed or two handed and ISL follows two handed style. It is used to represent words that have no sign equivalent or used to emphasize a word or is used in teaching/learning of sign language. Though fingerspelling usage is less [7], [8] in casual signing, they are an important component in sign language learning.

Sign Learning is very difficult for a beginner without the help of trained sign language practitioner. Learning through books is not effective as it is not easy to represent signs in a book using pictures. Though technology based tools exist for sign language learning, they do not provide any feedback on signs produced by the user. This makes it difficult to learn signs without any external help. Human resources [3]

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in this field is very less. Figures from India states that there are only 250 [9] interpreters ie, roughly one for every 20284 deaf people. Difficulty in understanding spoken language and its written forms, limited sign language proficiency of the teachers and the high expense [10] parents incur in educating their deaf child are factors that negatively affect sign language learning [11]. Apart from deaf people, parents, teachers, social workers and researchers need to learn signs. It is difficult for them to attend training programmes for learning signs. For hearing and speaking parents of deaf children, lack of learning mechanism coupled with their speaking ability makes them favor lip reading instead of using sign language. This makes it difficult for the child to communicate properly. Like many spoken language varieties, sign language has many regional variations. This is a problem for communication within deaf community itself. Our sign learning application helps to tackle that problem by helping to learn same standardized sign irrespective of the location of the participant. Major highlight of our application is that, user can learn signs without any external help.

SignQuiz is developed on the assumption that learning through practice will speed up learning. Unlike other existing mechanisms which need additional hardware which is costly, SignQuiz provides a low cost, machine learning based mechanism for learning signs. SignQuiz is available as a web based application. Sign language learner can learn signs using SignQuiz without any external help. Though there exists lots of research discussing machine learning based mechanisms for classifying signs, using sign classification as a tool for learning sign language is nonexistent.

Contributions of our paper are:

1) Development of a low cost sign learning framework
2) Application of Automatic Sign Language Recognition (ASLR) for Deaf education
3) Study on effectiveness of pretrained models for sign classification
4) Study on the effectiveness of technology enhanced mechanism as compared to traditional methods for sign learning

II. LITERATURE REVIEW

Technology based tools exist for both sign language learning and learning new concepts through sign language. Amount of interactivity provided by these tools vary. Though there exist tools that utilize Automatic Sign Language Recognition (ASLR) they require costly extra sensors for working. Large number of mobile based multimedia dictionaries exist for sign learning. Other than predictive searching and sign categorization they provide little interactivity. Virtual reality [12], [13] and game based mechanisms [14]–[16] were also explored for sign language based teaching/learning.

SMILE [17] is an ongoing project which aims to develop an assessment system for lexical signs of Swiss German Sign Language (DSGS) that relies on SLR. SMARTSign [18], [19] is a web based application for parents of deaf children for learning ASL. It has features such as sign dictionary, quiz, video recording functionality for learning. Game based [20], [21] mechanisms were also proposed for sign language learning. SmartSignPlay [22] is an extension of SMARTSign and provided a game based mobile application for sign vocabulary learning. Bouzid *et al.* [21] proposed a game based mechanism for learning sign language notation system SignWriting. Brashear [20] proposed a game based tool to develop deaf children's language skills. It provides interactive tutoring and real-time evaluation facility for learners. It was also equipped with camera and sensors for American Sign Language (ASL) recognition. The user wears gloves and any sign made will be captured by the camera. The system then shows a video with a signer demonstrating the correct ASL phrase. The user can then mimic these gestures. Kinect-Sign [23] is a Kinect based tool for learning sign language. Kinect-Sign runs in two modes; School mode and Competition modes to provide a quiz like environment for learning sign language. Adamo-Villani *et al.* [24] proposed a virtual learning environment for learning sign language mathematics and its related words. Along with the VR mode, it was also equipped with a gesture tracker for providing more user interaction. DICTA-SIGN [25] project explores a Human-Computer Interface (HCI) for deaf users with the help of sign-wiki project. Its main goal was to utilize Web 2.0 features for deaf users. It supports British Sign Language (BSL), German Sign Language (DDGS), Greek Sign Language (GSL) and French Sign Language (LSF). SignSpeak [26] project was proposed to develop a new vision-based technology for translating continuous sign language to text. This will help in communicating with hearing people. Virtual Signing Avatar based mechanisms were also proposed. ViSiCAST [27] (Virtual Signing: Capture, Animation, Storage, and Transmission) is a project funded under the European Union Fifth Framework to improve the quality of life of Europe's deaf citizens. It was built on experience gained from two projects which used virtual avatars Simon, Tessa and Visia. eSIGN is a EU-funded project whose aim was to provide information in sign language using avatar. The project has produced software tools which allow website and other software developers to augment their applications with signed versions. A notation system called SiGML was developed as part of the projects ViSiCAST and eSIGN.

Sign classification mechanisms mainly depend upon using data from external sensors [28], [29]. Most of them use data from Kinect or Leap Motion sensor for getting data. Others use a glove. These mechanisms have a practical limitation because it is necessary to use a costly extra hardware for getting data for sign recognition. With the advancement in deep learning, sign classification is possible from camera captured images itself. But research on practical tools using this is nonexistent. Deep learning based techniques provide low cost mechanism for development of sign language learning tools.

Available fingerspelling detection mechanism can be classified as those that need an external sensor [28]–[30] and those that works with the help of a simple camera. External sensors are used to capture depth and other orientation

TABLE 1. Comparison with different methods/application.

Method/Application	Accuracy	Hardware	Sign language	Signs
[37]	90.00%	Kinect and Leap Motion	Indian SL	25 3D Signs
[30]	97.85%	Kinect and Leap Motion	Indian SL	51 3D Signs
[33]	98.90%	8 IR camera and a video camera	Indian SL	500 3D Signs
[34]	99.00%	Camera	Irish SL	Finger Spelled
[36]	92.00%	Camera	American SL	Finger Spelled
[38]	86.00%	Camera	Japanese SL	Finger Spelled
[39]	93.00%	Camera	Japanese SL	Finger Spelled
[40]	98.90%	Camera	British SL	100 3D signs
[41]	92.00%	Glove	French SL	Finger Spelled
[42]	79.44%	Glove	Filipino SL	66 3D signs
SignQuiz	97.00%	Camera	Indian SL	Finger Spelled

information and uses specialized algorithms for classifying the signs. Of the classifying algorithms, machine learning based mechanisms are the most prominent ones. Most methods [28] using external sensors are based on Kinect [31] for capturing information. Indian Sign Language (ISL) recognition using HMM and BLSTM-NN was proposed by Kumar *et al.* [30]. In their approach they used both Kinect and Leap motion sensor for sign recognition. They have reported accuracies of 97.85% and 94.55% by combining HMM and BLSTM-NN for single hand and double handed signs respectively. They have also proposed an Independent Bayesian Classifier combination based approach [32] for ISL Automatic Sign Language Recognition (ASLR). Sign gestures were recorded using Leap motion sensor and a Kinect sensor was used to capture the facial data of the signer. Indian Sign Language recognition model using motion capture sensors was proposed by Kishore *et al.* [33]. They used a setup with 8 IR cams and a video camera. The signer must wear reflective markers on the body, which are captured by the system. They have reported an accuracy of 0.989.

Oliveira *et al.* [34] compared PCA and CNN based mechanisms for Irish Sign Language fingerspelled letter recognition. Recognition accuracy of 0.95 for PCA model and 0.99 for CNN model was obtained. Shi and Livescue [35] proposed a video based mechanism utilizing auto-encoder-based feature extractor and an attention-based neural encoder-decoder. They have reported a letter error rate of 8.1% for signer-dependent setting. Kim *et al.* [36] proposed a Deep Neural Network (DNN) based mechanism for sign recognition. They have achieved an average letter accuracy of 92% in signer-dependent setting.

Table 1 compares SignQuiz with other existing mechanisms. To the best of our knowledge SignQuiz is the only available application that works on Automatic Sign Language Recognition (ASLR) technique for ISL.

III. SIGNQUIZ DESIGN

SignQuiz is designed as a web based application that helps to learn signs without any external help. It is designed to work from any web browser so that users can access it without installing any new application. It works in two modes, learning and testing. In learning mode, signs are listed and one can learn the signs by clicking on the required ones. In testing mode, the user is tested for the learned signs. It is designed as a quiz application. User is asked to show a sign and system automatically detects the sign and gives feedback.

Automatic Sign Language Recognition (ASLR) forms the core of SignQuiz. Transfer learning [43] is used to tune our model to detect ISL signs. Transfer learning helps to train on new classes even if new training set is limited. In the case of transfer learning based approach, one trained model thought of as analogues to prior knowledge a human obtains from previous experiences, helps in learning new tasks more efficiently. In this mechanism, rather than starting with random weights, weights of a trained model is used for initialization. This helps as a better starting point for training rather than random initialization. Using an existing model and adjusting its weights according to our task, transfer learning helps to easily do ASLR. Our study reveals that it has got performance on par with the state of art classification models.

In the particular approach we followed, weights are kept intact for all the layers except last two layers and finetuned our model based on that. Penultimate layer contains a feature vector which is fed to a softmax layer. This softmax layer does the classification. Softmax classifier is mainly used in multi-class classification problem. Compared to a SVM classifier, Softmax classifier uses cross-entropy loss.

For a feature vector $Z^{[L]}$, the probability of each class is given by the Softmax classifier as

$$a^{[L]} = \frac{e^{Z[L]}}{\Sigma_{j=1}^{n} e^{Z[L]}}$$

where n is the number of classes. And

$$Z^{[L]} = W^{[L]}a^{[L-1]} + b^{[L]}$$

where W is weight vector and b is bias vector.

The softmax function $a^{[L]}$ returns a probability value for each class in the range [0,1].

In order to increase interest in user, testing mode is designed as a quiz application. User is asked to show a sign and then he can click on capture button to take picture. When user clicks on the button, after a delay few seconds, system captures sign shown by the user and gives feedback regarding whether the sign shown by him is correct or wrong. For example if user is asked to show sign "A" and if he shows the sign correctly, then user is given a feedback "A detected". If the user is asked to show sign ‘‘A’’ and if he shows the sign ‘‘B’’ instead, user is shown a message ‘‘B detected’’. As SignQuiz is modeled as a quiz application, correct answer is rewarded with five points and no point is given for wrong/incorrect answer. There may be a case where, user shows the sign, but his hand orientation is incorrect. This also happens when recognition system fails to correctly identify the sign due to clarity problems with the captured sign. This is reflected in the recognition score. In this case user is given the feedback ‘‘Can't detect sign’’. If the recognition score is below the given threshold, then user is asked to show the sign again.

Rather than trying to learn all the English letters in a single go, letters are learned in small groups. In SignQuiz group length is set as five. First, letters A-E are learned, then F-J and so on. This is modeled after the classroom teaching method followed for sign learning. Each sign is marked studied only if the user could show sign correctly two times. After each set is finished, a message about completion is given to the user and new set is taken. Learning procedure is shown in Algorithm 1. *signs* list stores list of alphabets to be studied. Initially first element from that list is moved to *study* list and learning takes place on that list. Variable *current* stores the current alphabet taken for study and variable *user_selected* is the sign recognized by the classifier. Parameter *threshold* stores accuracy threshold used for detection.

Algorithm 1 Alphabet Learning Algorithm

function ALPHABET(*threshold*)
  Select a random character from *study* list and store it in *current*
  while *signs* list is **not** empty **do**
    Select a random character from *study* list and store it in *next*
    if accuracy(user_selected) $\geq$ *threshold* **and** current==user_selected **then**
      sign_frequency of *current* is incremented
      score+=5
      if *sign_frequency* of *current* == 2 **then**
        Add *current* to *finished* list
        Remove *current* from *study* list
    else if accuracy(user_selected) $\geq$ *threshold* **and** current $\neq$ user_selected **then**
      score−=5
    else
      Print ‘‘Cannot detect sign’’
    if *study* list is empty **then**
      Select next set of alphabets from *signs* list
    current=next
  Return *score,finished*

IV. IMPLEMENTATION AND EVALUATION

A. DATASET

Finger spelled Indian Sign Language (ISL) signs were captured for training the model used for sign recognition. Capturing was done through mobile cameras, laptop camera and Digital SLR's. Signs corresponding to 20 fingerspelled alphabets were captured. This was collected with the help of 15 signers; 6 male and 9 female. Signers comprised students and faculty from Federal Institute of Science And Technology (FISAT), Kerala, India. They used signs released by Indian Sign Language Research and Training Center (ISLRTC) as a reference. The validity of the captured signs were confirmed by various sign language practitioners consisting of sign language interpreters, teachers and deaf people. Close to 1500 images were collected for each sign making the total number of images collected to about $20 * 1500$. Among the captured signs, certain alphabets like ‘‘A’’ and ‘‘B’’ are double handed and certain others like C are single handed.

B. IMPLEMENTATION

SignQuiz is designed as a web based application. Sign classification model and sign identification logic resides in the server. From the SignQuiz home page, user can select either training or learning feature. In the training screen, alphabets from A-Z are listed. In the learning screen user can show signs corresponding to given alphabets for learning.

Learning screen shows sign corresponding to English alphabets, current score and finished alphabet list. User can click on the capture button provided and can show the sign. A time delay is provided for sign capturing. After the sign is captured, it is send to the server from the browser. Image is captured within a two second delay to adjust for the lack of experience of the user in showing the sign. Server captures these images and finds out the alphabet corresponding to the sign. This is the output of the softmax classifier. Sign is accepted only if the accuracy is greater than 85%. Otherwise it is treated as an error. Figure 1 shows architecture of SignQuiz.

For simplicity, both learning and training screens are designed as a single screen. Image capturing and score update are done dynamically. This is made possible through client side scripting languages JavaScript and Ajax. Recognition result, score and other details are send back from server to browser in Json format.

SignQuiz used pre-trained models for sign classification. Two pretrained models - Nasnet and InceptionV3 were considered. Tensorflow [44] was used for implementation and training was done on HPE ProLiant BL460c Gen9 Server Blade which has Intel(R) Xeon(R) CPU E5-2640 v3 @ 2.60GHz.

For testing the effectiveness of proposed web based application, quantitative analysis was done. Quantitative analysis was based on testing 20 persons, of which 12 were female and 8 were male. These 20 persons were selected based on their willingness to take part in the study. They were trained on how to show signs in SignQuiz capture screen correctly. Research design followed was pre-test and post-test with control group and experimental group. From the group of 20 people, equal

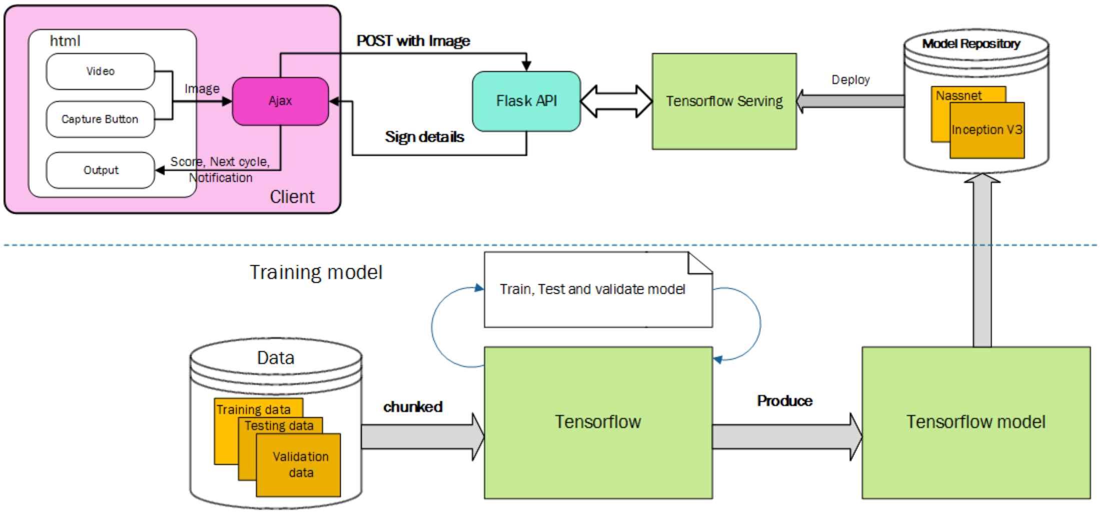


FIGURE 1. Architecture.

number are put into both groups randomly. These people had no prior ISL learning experience.

- Pre-test: In pre-test participants were asked to answer the same set of 15 questions to assess their vocabulary.
- Training: Participants in control group were trained using picture dictionaries and those in experimental group were trained using SignQuiz application.
- Post-test: In post-test the same procedure as in pretest was repeated.

For assessment, 15 alphabets are selected randomly and participants are asked to show the corresponding sign. This is evaluated by a trained instructor. Based on this, scores are given to the participants. For the particular mechanism followed in this study, for each correct answer 5 marks were given. Pre-test and post-test were conducted for both control group and experimental group.

Though there exist results that discuss classifier performance on test data sets, discussion on real life scenario is virtually nonexistent. As a learning mechanism we tested SignQuiz on different environments to find out how machine learning component behaves in different environments since it is very vital for using as an educational tool. For this data was collected from 14 different users and it included images in different settings. Users were asked to capture images from places where they were more likely to use SignQuiz. Images were captured through the same user interface as used by SignQuiz application. Sign images were captured in different orientations and light settings. Figure 2 shows sample images from the dataset.

V. RESULTS AND DISCUSSION

Figure 3 shows learning screen of SignQuiz where user can select alphabets. For each alphabet, images from front and back and video is provided. User can pause and replay the videos. Sign images from front and back side and video will help to clearly understand how a sign is produced.

Figure 4 shows training screen where user is asked to show signs. Sign to show, current score and completed signs are shown in a box. This gives information about progress.

Figure 5 shows the performance of two classification models studied - Nasnet and InceptionV3. For InceptionV3 model, recognition accuracy of 0.99 (cross entropy = 0.12) for training set and accuracy of 0.97 (cross entropy = 0.13) for validation set was achieved. For Nasnet model recognition accuracy of 1 (cross entropy = 0.12) for training set and recognition accuracy of 0.97 (cross entropy = 0.21) for validation set was achieved. For both the models, 8000 steps were used for training with initial learning rate fixed at 0.01. 10% of images were used for both test and validation set.

TABLE 2. Pre-test post-test result statistics.

		N	Mean	SD	Std Error Mean
Pre-test	Experimental Group	10	1.5	2.415229	0.7637626
	Control Group	10	2.5	5.400617	1.707825
Post-test	Experimental Group	10	54	11.73788	3.711843
	Control Group	10	34	18.52926	5.859465

Pre and post-test analysis given in the Table 2 shows that there is improvement in the mean scores of both the groups after study (Both classroom study and SignQuiz based study).

A null hypothesis was made that the scores of both groups were equal, and an alternative hypothesis was that the score of experimental group was significantly larger than that of control group. Before running t-test, normality of the scores was verified using Shapiro-Wilk normality test.

A paired one tailed t-test was done to understand the effectiveness of study on both experimental group ($t = 13.024$, $df = 9, p < 0.05$) and control group ($t = 5.0494$, $df = 9$, $p < 0.05$). Results shows that null hypotheses can be rejected. This confirms that learning (classroom and SignQuiz learning) improves the vocabulary understanding for both groups.

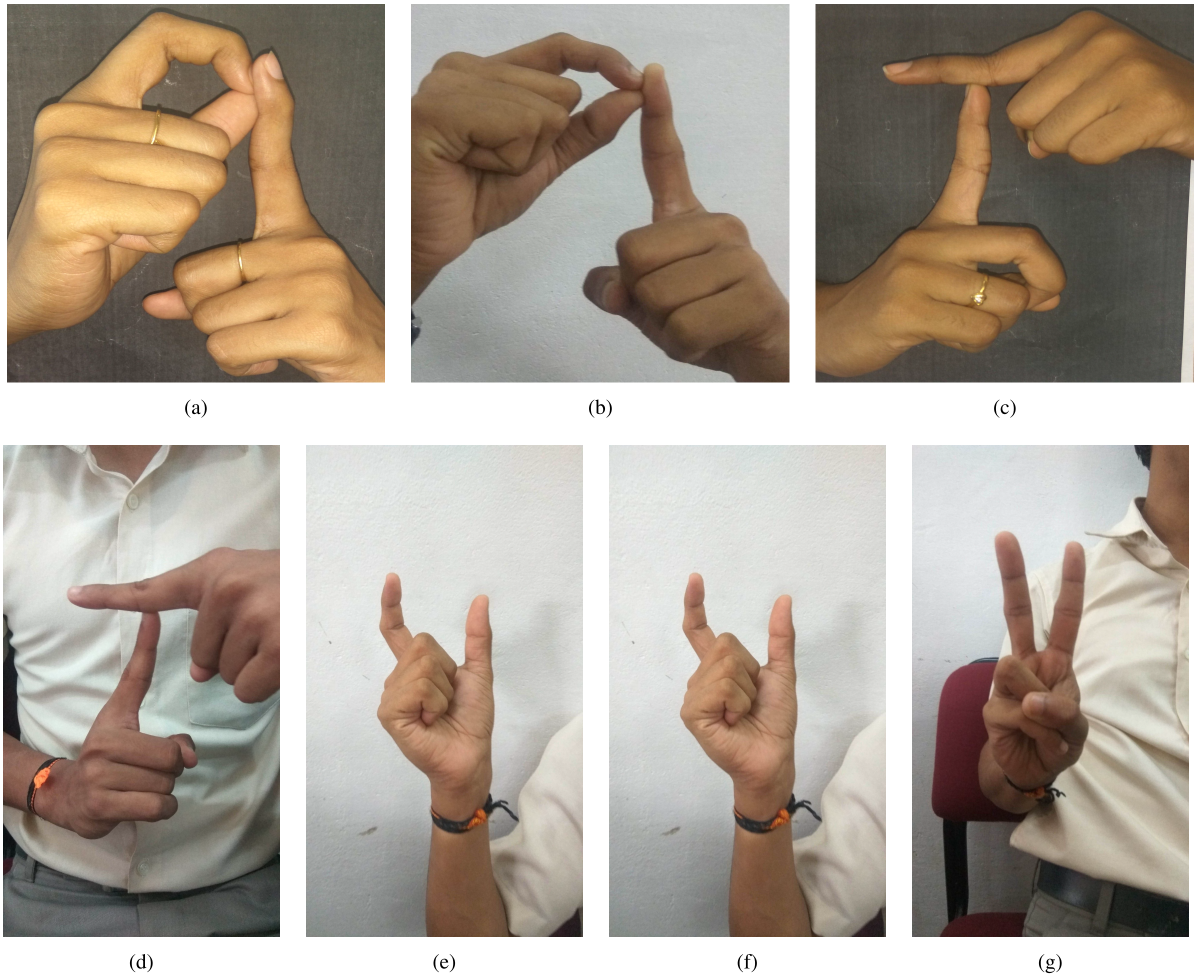


FIGURE 2. SignQuiz dataset sample images. (a) Alphabet P. (b) Alphabet P. (c) Alphabet T. (d) Alphabet T. (e) Alphabet U. (f) Alphabet U. (g) Alphabet V.

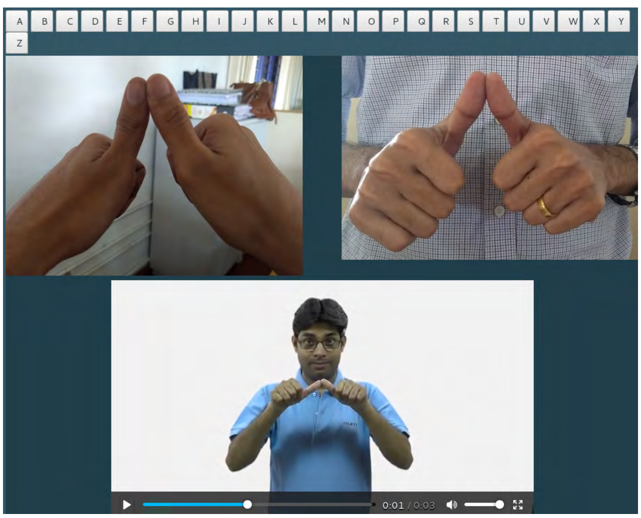


FIGURE 3. SignQuiz learning screen.

Gain scores for both groups were also calculated and compared. Our study has found that there is statistically significant difference between the gain score of experimental group and the control group. This indicates that SignQuiz has advantage in learning.

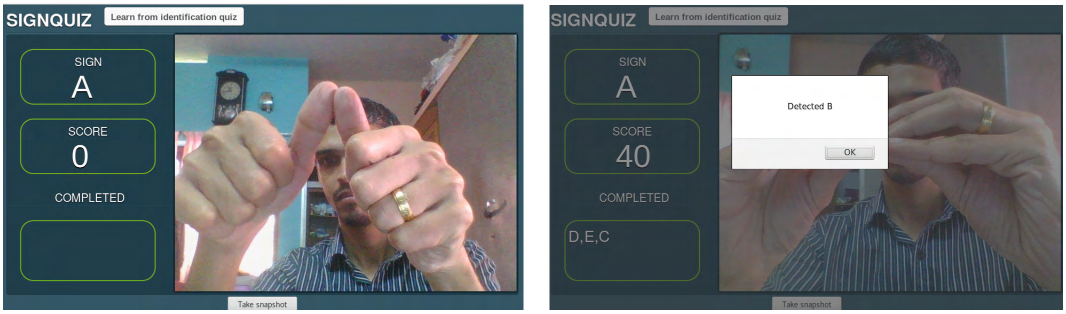
TABLE 3. Gain score summary.

Welch t-test					
Group	Mean	SD	df	t value	p-value
Experimental	52.5	12.74755	15.4	2.8274	0.006243
Control	31.5	19.72731			

Table 3 shows the gain score test result for the vocabulary test. One tailed unpaired t-test was used here.

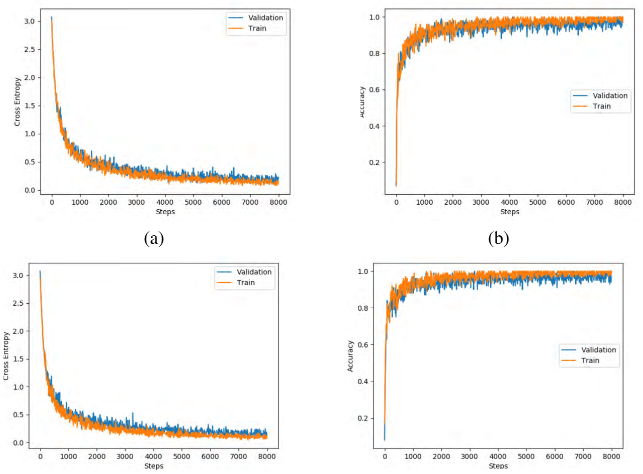
Analysis of gain scores shows that experimental group fares better as compared to control group in learning.

Our classifier was also tested on real life setting to find its effectiveness. For this, data was collected from 14 different users in different settings. By fixing detection accuracy threshold to 85%, users could use SignQuiz easily. For finding the threshold value, hundred images that were correctly shown by the users in the training set and fifty images that were correctly shown by the 14 users who took part in the SignQuiz real life testing were selected. Threshold value is



(a) (b)

FIGURE 4. **SignQuiz screens. (a) SignQuiz initial screen. (b) Sign detected and progress.**



(a) (b) (c) (d)

FIGURE 5. **Accuracy and cross entropy of Nasnet and InceptionV3 models. (a) Cross entropy - Nasnet. (b) Accuracy - Nasnet. (c) Cross entropy - InceptionV3. (d) Accuracy - InceptionV3.**

arrived at by finding the average of top 1 accuracy of these one hundred and fifty images. Before finding the threshold value, sign classification algorithm was run on the selected images and found out the precision to be 1. First time users found it difficult to show signs correctly on the SignQuiz screen. Detection accuracy fell below the threshold during this stage. When the sign shown by the user was not sufficiently close to fill the screen, it resulted in misclassification. For example when sign shown not filled the screen, classifier mistook sign "D" for sign "C". In another case, even though the showed sign sufficiently filled the screen, classifier mistook it for another sign, though with much lower top accuracy. Sign "A" shown by user is mistook for sign sign "C" by the classifier with accuracy 40%. SignQuiz handled this problem by showing the message "Sign not recognized" to the user.

VI. LIMITATIONS

SignQuiz tests were conducted on those people who volunteered to take part in it. Most of them are supporters of technology based applications. A bias towards technology based applications is obvious. SignQuiz currently included only finger spelled signs for learning. A full-fledged sign learning application needs to include more signs. For this purpose more study should be conducted to find out the effectiveness of gesture detection from videos. More detailed study needs to be done to find out the behavior of SignQuiz in signer independent setting. Currently signer independent data is limited to collecting signs from 14 users utilized for setting the threshold limit. SignQuiz is compared with printed ISL learning materials only. This is due to the absence of any other medium than peer learning for ISL learning.

VII. CONCLUSION AND FUTURE SCOPE

This paper presents SignQuiz, a web based application for learning sign language making use of Deep Neural Networks (DNN). SignQuiz application can easily be used by both deaf and non-deaf people. Ease of use, availability, low cost of operation are the features that make SignQuiz a useful application for learning finger-spelled signs.

By changing the model used, it can support any sign language. With proper training this application can easily include more signs. Usability can be improved if user can select alphabet range of his own choice for learning. Getting each user a user account will help to stop and start as he wish. This will also help to understand easy or difficult signs based on the global data. Rather than setting sign classification accuracy threshold globally, it can be set for each sign for better working. More detailed study should be done to set this. To make SignQuiz capture the sign made by the user without any external help, application is designed so as to wait for few seconds after user clicks on the capture button. This will create confusion in a novice user. Rather than putting the delay, showing a timer or automatically understanding that user has shown the sign and capturing it will be helpful.

We feel that results obtained from this study will help to design applications which are helpful in learning sign language.

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