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Interpreting Arabic sign alphabet by utilizing a glove with sensors

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***Abstract*---**People who are deaf or dumb in Arab communities face several challenges. The most important challenge is to communicate with people. In this study, a new approach for identifying the alphabet in the Iraqi Sign Language (IrSL) is proposed, which makes use of a suggested deep neural network called the Deep Recurrent Alphabet Sign Language (DRASL). It utilizes the Long Short-Term Memory (LSTM) technique for classifying the outputs and recognizing the alphabet in the SL. The dataset is constructed with the use of a glove that is coupled to flex sensors on each finger; each sensor gives a variable value based on the curvature ratio of the fingers. The sensors were connected to an Arduino which was then linked to a computer to transfer the data we collected. The data were divided into three groups, which had 29 different movements. All of these groups had a remarkably high accuracy equal to 100%.

***Keywords*---**deep learning, long short-term memory, recurrent neural network, sign language.

Introduction

The growing number of deaf-dumb people around the world is one of the biggest issues facing societies. According to the World Health Organization (WHO), there are now about 430 million deaf-dumb people in the world [W. H. Organization,2022]. It seems that there is weakness in dealing with such people, due to the lack of knowledge about how to understand them and how to benefit

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from their skills. This work is an attempt to fix this problem. Researchers have recent work that try to help the deaf-dumb community with the aid of latest technologies. There are many spoken languages and local dialects, so Sign Languages (SLs) also vary based on the spoken languages and their dialects. For example, Arabic Sign Language (ArSL) [Kamruzzaman, 2020], American Sign Language (ASL) [Tian, 2018], British Sign Language (BSL) [Kotowicz *et al*, 2021], German Sign Language (GSL) [Wienholz *et al,* 2019], and Chinese Sign Language (CSL) [Jiang *et al,* 2020] are all different. The hardest part of recognizing SL is to figure out how to understand hand gestures. In recent years, there has been a lot of interest in finding automated ways to detect hand gestures like images or sensors [Suri *et al*, 2020; Halvardsson *et al*, 2021].

Accurately recognizing hand gestures can help in building a strong system to understand the SL. Technologies that use manual engineering based on the Machine Learning (ML) can pick out important features [Johnny & Nirmala, 2022]. It is becoming more difficult to uncover powerful characteristics using old methods. In this study, our ultimate goal is to classify the sign languages in real-time. In order to achieve this, we first need an appropriate dataset. DL models have benefited from the fact that there are many different types of data in numerous domains thanks to millions of examples labelled for these fields [Simonyan & Zisserman, 2015; Krizhevsky et al, 2007; Tajbakhsh et al, 2016]. In contrast, there is almost a lack of data on the IrSL, we therefore collected and built a dataset ourselves. The data was taken using flex sensors attached to a glove, which captured the images of the hand gestures. The images were then transferred to and processed on a computer to form the dataset to be used. Based on the dataset, we built a deep learning model based on Recurrent Neural Network (RNN). This model, Deep Recurrent Alphabet Sign Language (DRASL), can automatically extract strong and effective features of the hand gestures and can then classify the gestures to individual alphabet with high accuracy in real-time. To summarize, the following contributions are made in this study:

- Collect and create a dataset of IrSL alphabet images using a sensor-binding glove.
- Propose a DRASL network model for extracting effective features and producing classification outputs.

The remainder of this work is structured as follows: Section 2 addresses the literature review, Section 3 presents the material and method, Section 4 analyses experimental outcomes; and Section 5 concludes the study.

Literature Review

A new technology using Android to develop the translation of the Indonesian Sign Language (INSL). The technology was developed to be able to convert the INSL into readable texts using a smart mobile phone. The texts could then be converted into audible sounds. A CyberGlove was exploited: it included 5 flexible sensors, an accelerometer, a built-in gyroscope and wireless communication based on Bluetooth. Not only the movements of fingers were required, but also the movements of hands. Dynamic Time Warping (DTW) is a method that uses a dynamic programming algorithm to calculate the distance between each input frame and a reference frame in order to determine the best pattern. DTW was implemented before the application was used on the mobile devices [Iqbal et al, 2017].

Spoken translation of GSL based on its own videos, in addition to using subtitles for SL videos. For both general and pre-specified settings, Sign Language Translation (SLT) was tailored in the context of Nervous System Translation (NST). This allows learning spatial representations, basic language models and speech signal assignments at the same time. For NST performance, raw data were collected from freely available data with a large vocabulary. The work was a combination of two types of networks, CNN for spatial modulation detection and a Recurrent Neural Network-Hidden Markov Model (RNN-HMM). With this combination, decoding was done to recognize and translate the video and convert it into spoken text [Camgoz et al, 2018].

A system that used human key point estimates for Korean Sign Language (KSL) translation. The SL dataset was provided by the Korea Electronics Technology Institute (KETI). It contained a high resolution and quality videos. A neural network model was used to extract human base points to convert SL videos into English words. Human base points were collected from the face and hands. An open-source project called Open Pose was used to discover ten human key points in real-time [Ko et al. 2020]. Hand gesture is a type of nonverbal communication that can be applied in a variety of studies including dumb and deaf communication, robot control, human-computer interaction (HCI), home automation, and medical applications. People can communicate via machines that use gesture recognition technology rather than relying on mechanical devices. The work aimed to recognize gestures and direct human movements to control specific devices. Two approaches to HCI applications were proposed. The first method of collecting data was based on gloves fitted with sensors. The second method was a computer vision approach that used camera vision to allow humans and computers to communicate [Selvarathi et al, 2020].

Developing a DL model called Gesture-Convolution Neural Network (G-CNN) to study Hindi Sign Language (HSL). The data was collected using an RGB camera, clipping only the shape of the gesture from the images and resizing it evenly before fusing it to the proposed neural network. The proposed model had fewer parameters, however, it achieved higher classification accuracy than the original CNN. In order to evaluate the proposed model, the results were compared in training and testing HSL data using the Visual Geometry Group (VGG), specifically VGG-11 and VGG-16. The training was performed on a publicly available set of ASL data. As a result of the study, the highest classification accuracy of HSL was obtained when using the proposed network. The main problem with HSL was the lack of publicly available data [Sharma and Singh, 2021].

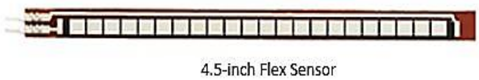
A study based on the development of artificial intelligence (AI) machine translator to classify new ArSL data that was used to extract new features from it. The proposed system could capture deaf-dumb SL images and translate them in real-time. Feature extraction was engineered for 40 manually selected traits and applied to four types of classifiers, Random Tree (RT), regression, bagging and

Random Forest (RF). The results showed that the performance of the RF classifier with the proposed extraction properties was better than that of others. The proposed work was carried out in two stages. In the first stage, the ArSL alphabet gestures images were preprocessed. More specifically, noise was removed, segmentation was normalized and dimensions changed. In the second stage, the model ran and output the results and the features [Latif et al, 2021]. To the best of our knowledge, there is no study on IrSL that utilizes a glove with sensors to interpret Arabic sign alphabet. This paper attempts to address this aspect.

Materials and Methods

Hardware Design

To collect Iraqi sign language gesture images, we invented a hardware, from which the IrSL alphabet dataset can be acquired. This will be illustrated below. Flex sensors are attached to glove fingers. A micro Arduino is used as a microcontroller. Its pins from A0 through A4 are utilized to read analogue values from flex sensors, where each flex sensor acts as a variable resistance. Figure 1 demonstrates such a sensor in this work. When the user showed different hand gestures, the level of bending of the fingers is different. The resistance value of a sensor is affected by bending. The more bent a sensor is, the larger the resistance value it has. For example, the sensor's resistance reads 62.5 Kilo-ohms (KΩ) when it is in the position of 45°, whilst it reads 100 KΩ when it is in the position of 90° [In-Depth, 2022]. There is a direct correlation between resistance curvature and the analogue resistance value. As a result of this feature, flex sensors can be very valuable in detecting a hand gesture.



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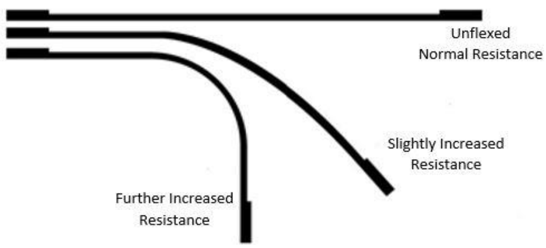


(b)

Figure 1. (a) Shape of a flex sensor and (b) Different flex sensor states

The flex sensors are connected in a voltage divider circuit. As the resistance changes in the sensor, the circuit outputs different voltages. The voltage divider circuit can be seen in Figure 2, where: V_{IN} is the supply voltage from Arduino, V_0 is the output voltage at the point between the resistors R1 and R6, and GND is the electrical circuit ground. The circuit outputs the voltages back to the Arduino via the analogue pin.

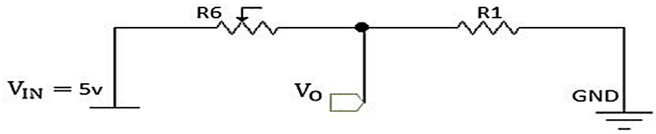


Figure 2. Voltage divider electronic circuit with the variable resistor (R6) of the flex sensor

The output voltage of the voltage divider electronic circuit can be calculated according to the following equation:

$$V_O = V_{IN}\left(\frac{R6}{R1 + R6}\right) \qquad (1)$$

Where V_O represents the output voltage to the analogue pin of Arduino, V_{IN} represents the input voltage supply from Arduino, $R6$ represents a variable resistor of the flex sensor and $R1$ represents a fixed resistor [Abraham et al, 2019]. Five flex sensors are connected to the five glove fingers. Figure 3 shows their full electronic circuit. In this figure, the resistors R1, R2, ..., R5 are fixed resistors, each have a value of 220 Ω; whereas the resistors from R6, R7, ..., R10 represent the variable resistors of sensors.

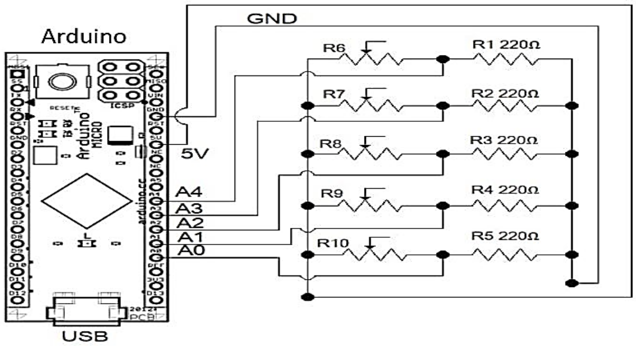
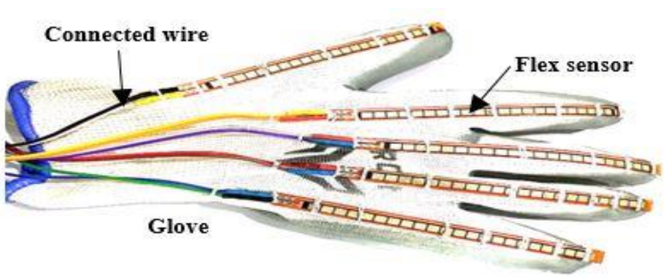


Figure 3. Full electronic circuit of how the variable resistors (R6, R7, ..., R10) of five flex sensors are connected to Arduino

Finally, the invented glove with sensors and how the sensors are connected to Arduino can be illustrated in Figure 4. They are used to acquire the dataset.



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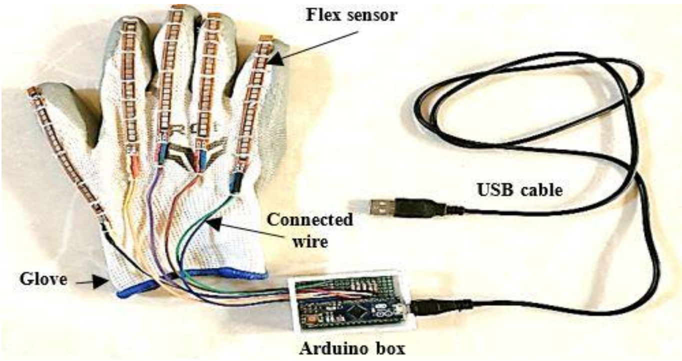


(b)

Figure 4. (a) Invented glove with five flex sensors, (b) Invented glove with five flex sensors connected to Arduino

Establishing the Dataset

Glove flex sensors deliver hand gestures data into Arduino via its serial port. Software program is adopted to read the data from Arduino. For each SL alphabet letter, 10 samples are considered. Thus, the dataset consists of 290 samples.

Proposed DRASL

We are to design a DL model, where the input is the IrSL Arabic Sign Alphabet (ASA) and the output is to recognize which Arabic letter the sign language refers to. There are 29 Arabic letters in total and the main task is to classify the distinctive hand gestures to the letters.

RNN

Before diving into our own model, we first briefly introduce RNN, which is the basis of our model. Each RNN has two main parts: the first part consists of a sequence of inputs and an LSTM layer, and the second part consists of fully connected (FC) layer, softmax layer and classification layer. Figure 5 shows the block diagram of a general RNN and its layers.

Figure 5. Block diagram of a general RNN

In the rest of this subsection, we will elaborate on each layer that will be used in our model.

Sequence Input

This is the first layer. It provides the input data entry. There are four types of RNN data input-output methods: one-to-one, one-to-many, many-to-one and many-to-many. Many-to-many have been approved according to work needs [Tavakoli, 2019]. Different RNN data input-output types are shown in Figure 6.

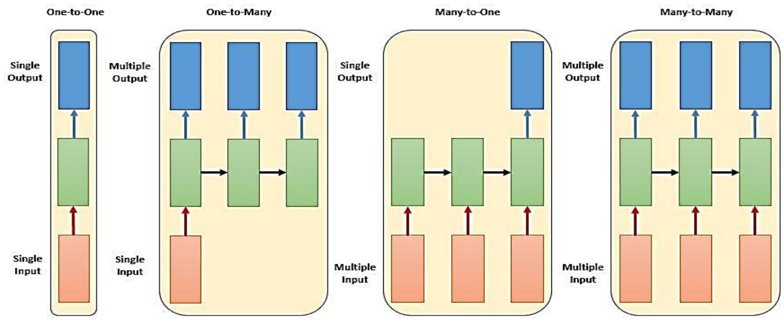


Figure 6. Different RNN data input-output types

Many-to-many method is used here. That is, the data are entered using multiple entries and assigned to multiple targets.

LSTM

this layer stores important information about the input for a long time and it can be removed if more analysis is provided. Actually, the LSTM learns which information to keep and which information to discard. Commonly, LSTM is made up of 3 gates: forget, input and output [Smagulova & James, 2019]. The forget gate is controlled by the sigmoid function, where its output value of 0 means that nothing can pass through and its output value of 1 means that everything can pass through. In the input gate, the sigmoid function decides which state values need to be changed by adding the new candidate values. This is done together with the following tangent hyperbolic (tanh) function:

$$\tanh(n) = \frac{1 - \exp(-2n)}{1 + \exp(-2n)} \qquad (2)$$

where $\tanh(n)$ represents the normalized output into the range (–1, 1), where n is the total number of sensor data. This function is to speed up the convergence process and it can prevent the cell memory from "blowing up" (exploding gradients problem) [Greff *et al*, 2019]. The other gate is the output gate, which determines the value of the output. Figure 7 shows the LSTM internal architecture. f_t is the forget gate of a previous cell state C_{t-1}, σ is the logistic sigmoid non-linear activation functions [Lee *et al,* 2020] and σ is applied on C_{t-1} to determine which the retrieved LSTM memory should be kept. tanh is then applied to the value between 1 and -1 (derived from the second sigmond function) with the following parameters: C_t a new cell state of the LSTM memory, and x_t a new input to the LSTM memory. Lastly, both sigmoid and tanh functions are applied again to determine the new output h_t.

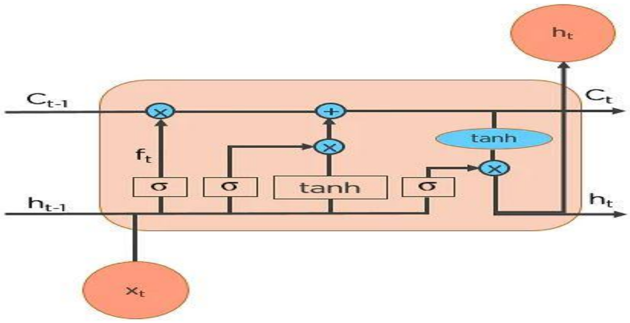


Figure 7. LSTM internal architecture

- **FC:** here each node in the previous layer is connected to all nodes in this layer.
- **Softmax:** this layer is utilized to offer the corresponding probability distributions to all classes for a given input.
- **Classification:** it is the last layer that provide the classification outputs. It follows the winner-takes-all rule.

DRASL

The deep neural network we proposed is called the Deep Recurrent Alphabet Sign Language (DRASL). It consists of three RNNs, each of which can accept a group of distinct hand gestures. The reason that we need three RNNs is because some letters have similar movements or gesture forms. The overall architecture of our model is shown in Figure 8.

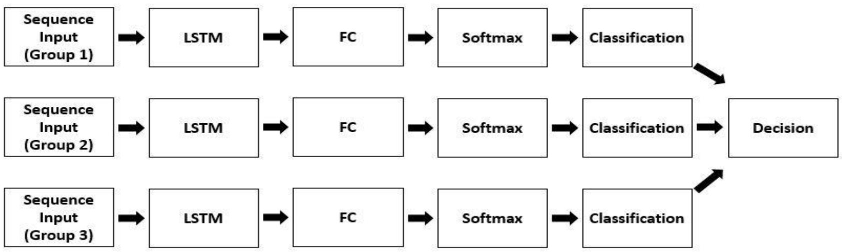


Figure 8. Block diagram of the proposed DRASL

To illustrate, similar letters of hand gestures have been assigned to different groups. The DRASL interprets a gesture based on its target. It can deal with certain targets that are related to certain inputs. As other Machine Learning (ML) models [Al-Kaltakchi *et al*, 2018; Al-Nima *et al*, 2008, 2010, 2020, 2021; Khalil *et al*, 2009; Al-Kaltakchi *et al*, 2020] the DRASL requires two phases: training and testing. Training phase will firstly start before the testing phase.

Results and Discussions

Established Dataset

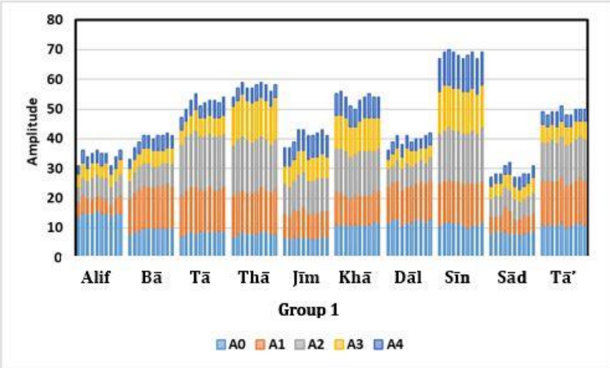
The data collection took place from the 2nd of March 2022 to the 29th of May 2022. Initially, data from the five sensors that were attached to glove fingers were collected. They represented hand gestures for the IrSL as a case study. Each sample contained five values from the five sensors. There are 29 letters in the Iraqi (sign) language in total and 15 samples were provided for each letter. A total number of 435 samples of data for right-hand gestures were generated.

Standardizations

Certain standardizations can be applied for different techniques [Hamdany *et al*, 2019; Al-Nima *et al*, 2021; AL-Hatab *et al*, 2020; Abuqadumah *et al*, 2020; Al-Kaltakchi *et al*, 2018]. Here, all experiments were carried out on a laptop with the following facilities: type Dell, Intel Core i7 processor, 2.20 GHz processor speed, 8 GB computer memory, NVIDIA external graphics card, GF117 Graphics Processing Unit (GPU) and 2 GB display memory. The dataset contained 435 samples, which were divided into three groups. Each group represented distinct hand gestures that can be accepted by an internal RNN inside the DRASL, as mentioned. The separation was done to eliminate the interference with the signals of values obtained from the glove. Furthermore, experiments were considered for the following training criteria: Adaptive moment estimation (Adam) optimizer, gradient decay factor value equal to 0.9 and initial learning rate equal to 1×10^{-3}. Dataset was partitioned into training and testing, where 290 samples were used for training and 145 samples were for testing. The number of output classes was limited to 29, each of which represented an interpreted ASA letter.

DRASL Parameters

Multiple experiments were carried out to assign the appropriate inputs and parameters for the proposed DRASL network. Determining inputs and parameters were logically done to find out their appropriate values. Figure 9 shows different amplitudes of various experiments on the three grouped distinct hand gestures that are applied to the proposed DRASL network. This figure includes values from the Arduino analogue input pins (A0, A1, A2, A3 and A4), which represent the bends of five sensors.



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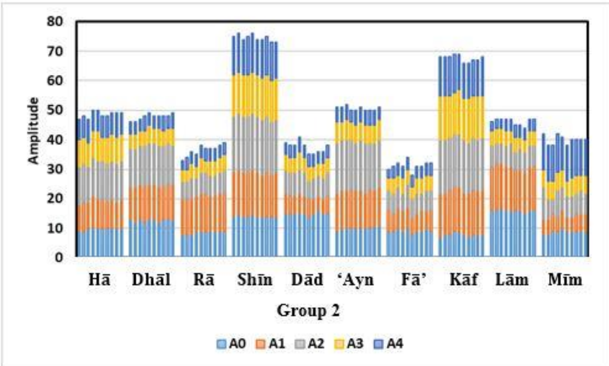

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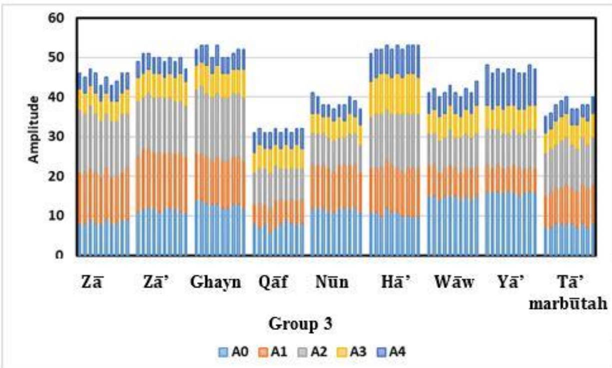

(c)

Figure 9. Different amplitudes of various experiments on the three grouped distinct hand gestures that are applied to the proposed DRASL network: (a) Group 1 accepts 10 letters, (b) Group 2 allows 10 letters and (c) Group 3 takes 9 letters

Figure 9 demonstrates that each ASA letter has distinct values which can describe distinct hand gesture. However, there are different letters that have similar values which may describe similar hand gestures. Therefore, ASA letters are separated into three groups, each group assigns to certain letters. Number of hidden units for the three groups is found after changing its parameter to be equal to 100 nodes. Mini-batch size values are investigated to be 25 for groups 1 and 2, and 15 for group 3. Numbers of epochs are explored as 100 epochs for groups 1 and 2, and 300 epochs for group 3. Such parameters lead the DRASL to achieve a very high accuracy.

Training

Training was performed for 290 samples of the dataset. That is, group 1 and 2 used 100 samples each, and group 3 exploited the remaining 90 samples. Training performances of the proposed DRASL are given in Figs. 10, 11 and 12 for the three groups.

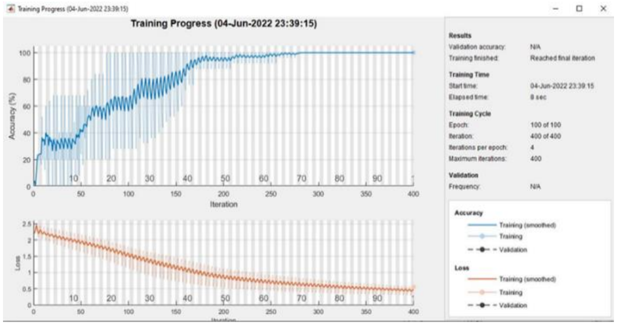

Figure 10. Training performances for group 1

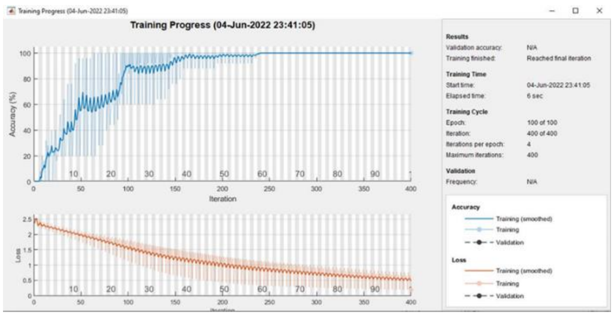

Figure 11. Training performances for group 2

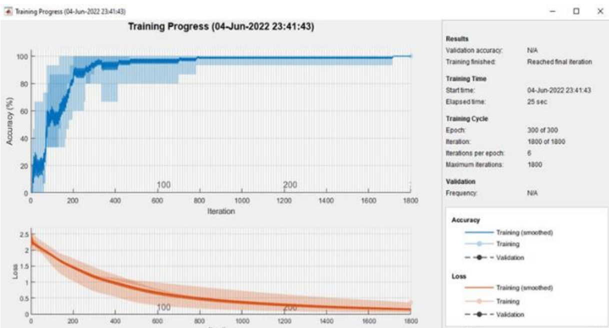

Figure 12. Training performances for group 3

These figures show the curves of training accuracies, curves of training losses (errors) and numbers of iterations. Basically, each figure demonstrates two curves: the first one displays the relationship between the percentage accuracy and iteration, and the second one displays the relationship between the loss (error) and iteration. All trainings are successfully implemented as the accuracies are maximized and losses are minimized.

Testing

Tests were performed for 145 samples for three groups. Here, the DRASL was evaluated according to the determined parameters, as illustrated in subsection *training*. A very high accuracy of 100% is benchmarked.

Conclusion

This paper presented an invented glove with sensors that was designed to interpret ASA. The glove was made available to be worn by humans. Then, the finger movements will be detected and linked to a computer through the Arduino. The dataset was acquired from scratch. Multiple readings of the amplitude were collected for each hand gesture of an ASA letter. Up to 29 Arabic letters were considered. For each letter, a hand gesture movement was repeated more than 15 times. Then, all the data were divided into training and testing sets. A new approach called the DRASL was proposed. As some letters have close gesture forms, the DRASL contained three RNNs to separate the close gesture forms. Each RNN accepted certain values for a group of distinct ASA hand gestures. This model could successfully achieve a remarkably high accuracy of 100%. To the best of our knowledge, the overall work of this paper is novel for the case study of the IrSL.

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