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RESEARCH ARTICLE

Enabling Two-Way Communication of Deaf Using Saudi Sign Language

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ABSTRACT Disabled people are facing many difficulties communicating with others and involving in society. Modern societies have dedicated significant efforts to promote the integration of disabled individuals into their societies and services. Currently, smart healthcare systems are used to facilitate disabled people. The objective of this paper is to enable two-way communication of deaf individuals with the rest of society, thus enabling their migration from marginal elements of society to mainstream contributing elements. In the proposed system, we developed three modules; the sign recognition module (SRM) that recognizes the signs of a deaf individual, the speech recognition and synthesis module (SRSM) that processes the speech of a non-deaf individual and converts it to text, and an Avatar module (AM) to generate and perform the corresponding sign of the non-deaf speech, which were integrated into the sign translation companion system called Saudi deaf companion system (SDCS) to facilitate the communication from the deaf to the hearing and vice versa. This paper also contributes to the literature by utilizing our self-developed database, the largest Saudi Sign Language (SSL) database—the King Saud University Saudi-SSL (KSU-SSL). The proposed SDCS system performs 293 Saudi signs that are recommended by the Saudi Association for Hearing Impairment (SAHI) from 10 domains (healthcare, common, alphabets, verbs, pronouns and adverbs, numbers, days, kings, family, and regions).

INDEX TERMS Avatar, Saudi Sig language, speech recognition system, sign language recognition.

I. INTRODUCTION

The hearing disability has resulted in the isolation of individuals with deafness from mainstream society, leading to their confinement within the deaf community. Consequently, they face significant challenges in accessing basic services such as government departments, hospitals, airlines, and banks. This issue is particularly pronounced among the elderly, as they may struggle to physically visit service providers and face difficulties obtaining services remotely. In 2021, the World Health Organization (WHO) reported that approximately 1.5 billion people are living with hearing loss, of which 430 million people have disabling hearing loss [1]. In Saudi Arabia, data from the 2017 Demographic Survey

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conducted by the General Authority for Statistics reveals that 7.1% of the population, equivalent to 1,810,358 residents, are living with a disability [2]. Sign language serves as the primary and natural language for deaf individuals, while the spoken language of their respective countries becomes their second language (L2). This foundation has given rise to the Bilingual/Bicultural philosophy, which posits that sign language should be used to teach the L2, rather than relying on the language used by the surrounding community. Consequently, the importance of linking language with culture arises, as Deaf children can be introduced to hearing culture through sign language, facilitating their integration and learning within society. However, the majority of deaf individuals do not have the opportunity to learn sign language at home. Research has demonstrated that approximately 90% of deaf children are born to hearing parents who are unfamiliar with Deaf culture and lack knowledge of sign language [2], [3]. Therefore, deaf children primarily acquire their first language at the school level [4]. Unfortunately, the situation becomes more challenging for these children within the school environment. Saudi Vision 2030 places emphasis on providing the necessary facilities and resources to empower disabled individuals to receive education and employment opportunities, enabling their independence and integration as active members of society [5]. In Saudi Arabia, the estimated number of deaf individuals is approximately 720,000 [6]. Deaf individuals face significant difficulties in communicating with others in society, as only a small number of them possess knowledge of and utilize sign language for communication. The scarcity of sign language interpreters further exacerbates their challenges in interacting with the broader community, particularly when accessing government services such as healthcare, schools, courts, and airports [6].

In general, deaf individuals use sign language or text to interact or communicate with others. While these methods are effective within the deaf community, they face significant limitations when trying to communicate with the hearing community. This can lead to isolation, frustration, and discrimination. The proposed system aims to address these gaps by providing a two-way communication solution between deaf individuals and the rest of society. The use of avatars to perform Saudi sign language (SSL) can have a significant impact on involving deaf individuals in education, healthcare, and society. The proposed SDCS can empower deaf students with real-time sign language interpretation, facilitating their active participation and comprehension of academic materials. In healthcare, the system bridges communication gaps between deaf patients and healthcare providers, enhancing the quality of medical consultations and ensuring accurate information exchange. In general, SDCS enables people who do not know sign language to communicate with the deaf community. With avatars, non-signing individuals can input their message, and the avatar can translate it into sign language. This technology thus bridges the gap between the deaf community and the hearing community, enabling better communication and understanding. Additionally, the use of avatars for SSL can be especially impactful in areas where sign language interpreters are scarce. In many cases, deaf individuals struggle to communicate because they do not have access to interpreters. The use of avatars can therefore be a valuable tool for providing access to sign language interpretation, regardless of a person's location. Furthermore, avatars can help deaf individuals to become more integrated into society. By providing a means for communication, this technology enables deaf individuals to participate in various settings, including educational, vocational, and social environments. As a result, the deaf community can enjoy greater opportunities for personal and professional development. In general, AI has made significant advancements in recent years, particularly in the field of natural language processing (NLP). This technology has the potential to revolutionize the way we communicate and bridge language barriers between individuals. The objective of this research paper is to utilize AI to develop a translation system that can automatically recognize the SSL and convert Saudi speech and text to avatars. This system involves a speech recognition module that processes the speech of a non-deaf individual, which is then fed into text and avatar sign generation modules to generate and perform the corresponding sign of the original speech.

The main contribution of this study is to develop and build the deaf companion System (SDCS) to enable two-way communication between non-deaf and normal people in Saudi sign language. To do that; first, we built and developed a Saudi sign language database (KSU-SSL) that contains videos of 293 Saudi signs that are recommended by SAHI from 10 domains (healthcare, common, alphabets, verbs, pronouns, and adverbs, numbers, days, kings, family, and regions). Second, we designed and developed a high-performance sign recognition module for the 293 signs. Third, we designed and developed a speech synthesis module for any text. And fourth, we developed the avatar module for the 293 signs and more. We then integrated the different modules into a complete system called SDCS. Overall, this research paper represents a significant step forward in the development full two-way communication system for the deaf.

This paper is organized as follows. First, a literature review is presented. Second, the database is described. Third, the proposed system components are described. Fourth, the integration and experimentation results are illustrated and discussed.

II. LITERATURE REVIEWS

Based on the objective of this study, we will review the literature for the different areas. The sign language perspective of a sign specialist shows the need for the solution that will come out of this study; then, we will review the available sign language dataset, the single recognition techniques, the Arabic speech recognition techniques, and then, the using of avatar.

TABLE 1. Multiple difficulties for the Saudi Population by Type of Disability and Cause of difficulty [7].

Cause of Disability	Difficulty								
	Total	Communication and understanding others	Memory and connection (cognition)	Difficult to walk or climb stairs	Hearing		Personal care such as bathing, dressing or using the toilet	Seeing	
					With the use of audio aids	Without the use of audio aids		With the use of glasses	Without using glasses
Congenital	14.84	21.59	17.4	12.56	15.22	19.23	14.72	11.74	14.66
During Pregnancy	1.99	3.92	2.86	1.34	1.31	2.91	3.45	0.97	0.89
During Delivery	5.38	13.34	8.75	3.74	2.17	3.99	9.39	1.75	1.82
Traffic Accident	2.93	2.5	3.1	3.41	1.81	1.92	4.03	2.98	1.65
Other Accident	5.93	5.41	6.33	6.01	6.12	4.94	4.37	7.14	6.07
Disease	54.02	44.03	50.06	56.28	56.75	53.4	51.18	56.81	59.54
Other	14.91	9.21	11.5	16.67	16.61	13.62	12.86	18.6	15.36
Total	1810358	185508	203295	527269	172460	57081	227609	269554	167582

TABLE 2. Existing ArSL datasets comparison.

Ref	Year	signers	signs	Repetition/ signer	Samples	Recorded expert
SCHS-Dateset [8]	2007	3	23	50	3450	No
KFU-Dateset [9]	2007	1	300	15	4500	No
SignsWorld Atlas-Dataset [10]	2014	10	500	-	-	No
ArSL-ElBadawy [11]	2015	2	20	100	4000	No
ArSL2018-Dataset [12]	2018	40	32	42	54049	No
ArSL1800-Dataset [13]	2001	-	30	60	1800	No
[14]	2012	2	6	15	180	-
[15]	2013	-	-	-	948	-
[16]	2016	2	28	15	840	-
AUE-Dataset [17]	2008	1	80	19	1520	-
Tolba-Dataset [18]	2012	-	100	-	100	-
Our	2022	33	293	5	145035	Yes

In recent years, multiple datasets for Arabic Sign Language (ArSL) have been published. The ArSL dataset introduced in 2007 by the College of Engineering at the American University of Sharjah (SCHS-Dateset) [8] is an isolated words dataset. It comprises 23 gesture classes performed by three participants, with no restrictions on image background or clothing. Each participant repeated the gestures 50 times across three sessions, resulting in a total of 3450 samples. Another ArSL dataset was introduced by Mohandes et al. in 2007 at King Fahd University of Petroleum (KFU-Dateset) [9]. This dataset includes 300 classes. A single hard-of-hearing fluent signer recorded each sign 15 times, resulting in a dataset of 4,500 samples. In 2014, the SignsWorld Atlas dataset for ArSL images and videos was introduced by Shohieb et al. [10]. It includes handshapes in isolation and single signs, Arabic alphabets, numbers, movement in single signs, movement in continuous sentences, lip movement in Arabic sentences, and facial expressions. The dataset was performed by 10 participants, aged three to 30 years, under controlled lighting conditions. Another ArSL dataset introduced in 2015 [11] includes 20 gesture classes performed by two participants. Each participant repeated the gestures 100 times. The 20 signs include five facial expression signs: happy, sad, normal, surprised, and looking up. Latif et al. developed the ArSL2018 dataset [12], which is an image-based dataset for 32 Arabic alphabets, including the basic 28 alphabets and the extended four alphabets ('ال', 'أل', 'ة', 'ئ'). ArSL1800 [13] is another ArSL dataset comprises 54,049 grayscale images with dimensions of 64 × 64. The images were collected by recording 40 participants in different lighting conditions and backgrounds. Other datasets include a dataset of 1800 grayscale images for 30 Arabic alphabets, a dataset of 180 grayscale images for six signs [14], alphabet datasets with 948 and 840 sign samples [15], [16], a dataset of ArSL for 80 sentences [17], and a dataset of 100 sentences for continuous sentence recognition [18]. By contrast, 140 of the ASL dataset reported in [19] consists of 80 gesture classes. It was created by 141 the Center of Smart Robotics Research.

The dataset comprises selected gestures from 142 common ArSL words and expressions. These expressions contain single- handed actions 143 as well as two-handed actions. In Table 2, we provide a comparison between the surveyed databases mentioned above and our proposed KSU- SSL dataset.

Experts in [20] stated, ''Language is culture, a product and manifestation of culture''. (p. 118) Like any other community, Deaf (with capital D to represent Deaf culture) people have their own culture, and sign language is the essence of their culture. sign language is different from one country to another, just like spoken languages, even if the commonly spoken language in two countries is the same [21]. For example, although the commonly spoken language in the United States and the United Kingdom is English, American Sign Language and British sign language have significant visual-manual modality differences as each is based on the culture in each country. This remark applies also to Arabian countries. Sign language is the first and native language of Deaf people, while the spoken language in whatever country they live in is their second language (L2). As a matter of fact, Bilingual/ Bicultural philosophy emerged from the previous point. The bilingual-bicultural approach is based on the premise that sign language is the first and natural language of a Deaf child [22]. The idea is that the L2 is taught through sign language and not through the language of the community in which they live. Ultimately, this requires the linkage of language with culture and introducing Deaf children to hearing culture through sign language, allowing them to better integrate and learn in that society. However, most deaf people do not have the opportunity to learn sign language at home. To elaborate, research has proved that approximately 90% of Deaf children are born to hearing parents who are not familiar with Deaf culture and do not know how to use sign language [2]. Therefore, Deaf children learn their first language at the school level [4]. Conversely, the scenario becomes worst at the school level for these children. Accordantly, One effective way to enhance the communication and education of Deaf people is through using technology such as automatic translation programs from speech to sign language and vice versa.

From the techniques point of view, scientists and researchers used machine learning (ML) and Deep learning (DL) in several applications including medicine [23], [24], [25], sign language [19], [26] agriculture [27], text sentiment analyses [28], robotics [29], [30], etc. From the recognition techniques point of view, deep learning has become the dominant technique in general sign language recognition [31], [32], [33] and in automatic speech recognition (ASR) hence we focus here in only on the latest research based on DL. [34], [35] developed an Arabic ASR system based on 200 hours from GALE [36]. GALE is one of the largest Arabic corpora developed by the Linguistic Data Consortium (LDC) [36].They used conventional and a deep neural network acoustic models. Long short-term memory (LSTM) and gated recurrent unit (GRU) are used for Arabic speech recognition [37]. Deep auto-encoder was used in [38], for remote Arabic speech recognition system. The authors used isolated words Arabic speech database for their experiments, where the database contained only a recording of 20 words. To build an ASR system, a lot of ASR toolkits are released such as Kaldi [39], Baidu's Deep Speech from Mozilla [40], wav2letter from Facebook [41], PyTorch-Kaldi [42], openseq2seq from Nvidia [43], and ESPnet [44].

On the other side many studies have used the avatar for displaying Arabic signs, In reference [45], a system was developed to translate Arabic sign language. This system translates words into the Hamburg notation system, which categorizes the hand shape, orientation, location, and movement as manual parameters. Simultaneously, facial expressions, shoulder elevation, mouthing gestures, hand tilting, and body movements are categorized as non-manual parameters. These signs are subsequently transformed into a sign gesture markup language file, which is then enacted by a 3D avatar. Reference [46] introduced an avatar-based translation system for Arabic sign language, in this system an Arabic sign language 3D motion database was recorded using data gloves, then an avatar will animate the signs. In [47] a mobile-based communication framework for Arabic sign language was presented, in this system a 3D motion database of 588 signs was created using synthetic animation where the user can exploit a sign-editor to create the video representation of the signs. In [48] the authors present a machine translation system based on rule-based interlingua and example-based approaches. The system uses SAFAR platform [49] and ALKHALIL morpho system [50] to extract the morphological properties of the words, then it generates a video sequence to represent the word in Arabic sign language. In [51] the authors develop an application that translate Arabic text into Arabic sign language and vice versa. If the user is non-deaf he can write a text then the application will translate it to sign language using 3D avatar, and if the user is deaf he can select a sign from the database and the application will translate it to text. Moreover, several research has been introduced for translation from SSL to speech and text.

In conclusion, we noticed that applying End-to-End (E2E) ASR for the Saudi speech recognition system still needs more investigation. Moreover, there is no avatar-based system for SSL.

III. KSU-SSL DATABASE

To ensure the accuracy and relevance of the our self-proposed Database [52], we used the latest version on the Saudi sign dictionary introduced by the SAHI, with input from our team of sign language experts. As illustrated in Table 3, the selected signs belong to 10 different domains. The proposed dataset consists of 293 signs selected by sign language experts, performed by 33 people, and repeated five times for each. The proposed dataset was recorded using three different cameras: mobile camera, IR, and RGB cameras to enhance the richness and versatility of the database to use in various applications. The proposed dataset consists of a total of about 145,035 (293 "signs" * 33 "people" * 5 "repeating" * 3 "cameras") samples (as shown in Table 3).

TABLE 3. Database statistics.

Signs #	Signers	Domain	Rep	Cam.	Samples	%
133	33	Healthcare	5	3	65835	45.4
39	33	Common	5	3	19305	13.32
37	33	Alphabets	5	3	18315	12.6
20	33	Verbs	5	3	9900	6.83
18	33	Pronouns	5	3	8910	6.15
11	33	Numbers	5	3	5445	3.76
11	33	Days	5	3	5445	3.76
9	33	Kings	5	3	4455	3.08
8	33	Family	5	3	3960	2.74
7	33	Regions	5	3	3465	2.39
Total **Signs 145035**						100

IV. PROPOSED SAUDI DEAF COMPANION SYSTEM (SDCS)

In an effort to facilitate the inclusion and societal integration of individuals with hearing impairments, we have developed the SDCS system (depicted in **Fig. 1**). This system enables a two-way translation of Saudi sign language, aiding effective communication. The SDCS system can be seamlessly integrated into portable electronic devices such as laptops, tablets, or mobile phones. It comprises three essential modules (SRM, SRSM, and AM). SRM is responsible for identifying and interpreting the signs made by individuals who are deaf, subsequently generating corresponding text. The SRS Module plays a vital role in recognizing spoken language. It takes the speech as input from individuals with normal hearing and converts it into text format. AM contributes to the system by converting the recognized text from the spoken language of individuals with normal hearing into sign language. This conversion is then visually represented through an avatar, enabling individuals with hearing impairments to comprehend the spoken language of those without hearing limitations. Each of these modules is designed to execute specific tasks, collaborating with one another to operate the SDCS system seamlessly.

A. SIGN RECOGNITION MODULE (SRM)

The SRM is designed to enable individuals with normal hearing to comprehend the gestures of those with hearing impairments. This is achieved through the SRM's ability to identify and interpret the signs executed by individuals who are deaf, generating relevant textual output.

Furthermore, the SRM facilitates the conversion of the recognized sign-based text, which the deaf individual performed, into spoken language. Within our proposed SRM, We used a self-developed concise 3D Graph Convolutional Network (3DGCN) featuring a limited number of trainable parameters. This strategic design ensures efficient representation learning, allowing for effective performance while maintaining compactness.

The proposed architecture consists of five consecutive layers of separable 3D Graph Convolutional Networks (3DGCN), which are divided into spatial and temporal convolution operations through the utilization of a spatial multi-head self-attention layer, as depicted in **Fig. 2**. A residual connection connects the input layer to the output layer. For spatial convolution, this approach considers the spatial neighborhood of each node to include all nodes within a single step distance from that particular node. For more details regarding our proposed 3DGCN, please refer to [26].In order to extract the essential graph nodes for recognition purposes, we made effective use of MediaPipe [53], a powerful human landmark estimator. Our approach was further enhanced for optimized learning efficiency through the incorporation of methodologies like multi-head, self-attention, and frame node partitioning. The wide spectrum of applications that MediaPipe caters to in contemporary life includes augmented reality, fitness, and sports analysis. It boasts the capability to precisely identify and track 33 pose landmarks, 21 landmarks per hand, and 468 facial landmarks using diverse solutions. The cohesive models integrated within MediaPipe provide an encompassing solution, estimating and tracking a total of 543 landmarks across x, y, and z coordinates. This is exemplified in **Fig. 3**, which showcases a representative frame from the proposed dataset. To achieve a balanced equilibrium between recognition precision and computational complexity, our focus was on the 25 most pertinent landmarks during the construction of the sign graph. Specifically, out of the 21 landmarks depicted in **Fig. 4-a**, we meticulously selected ten landmarks for each hand, as illustrated in **Fig. 4-b**.

Furthermore, we incorporated an additional set of five landmarks that encompassed the nose, shoulders, and elbows. Notably, the nose landmark was strategically utilized as a reference point to facilitate the normalization of landmarks for each individual frame.

B. SPEECH RECOGNITION AND SYNTHESIS MODULE (SRSM)

The proposed **SRSM** is used to recognize the speech of a normal person and produce the corresponding text. To convert from speech to text, we used Kaldi toolkit because it supports the available training steps of GALE database [34]. And we used the best acoustic model which was Time Delay Neural Network (TDNN) model. To test the performance of the trained acoustic model in this domain, we asked two different Arabic native speakers to pronounce the words of our proposed Database. Additionally, the proposed SRSM

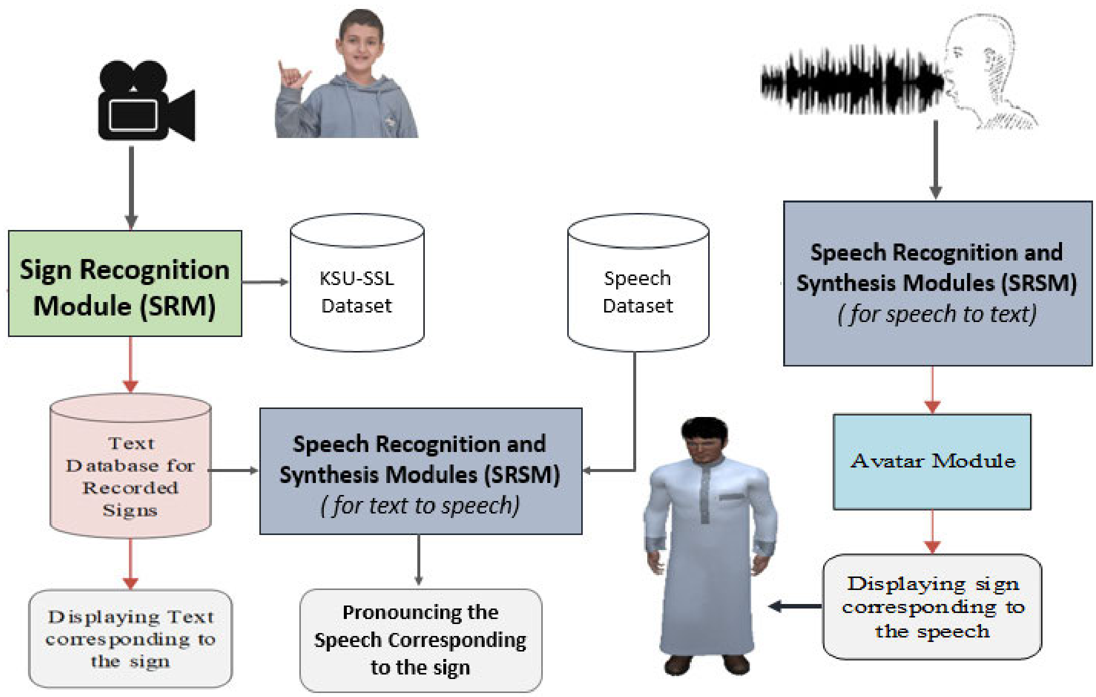


FIGURE 1. Proposed deaf companion system (SDCS).

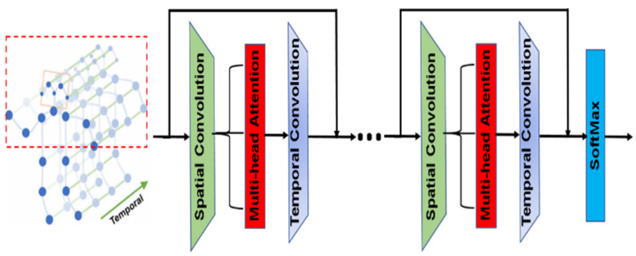


FIGURE 2. The proposed 3DGCN architecture.

FIGURE 3. Landmarks extracted from MediaPipe (excerpt from our suggested dataset).

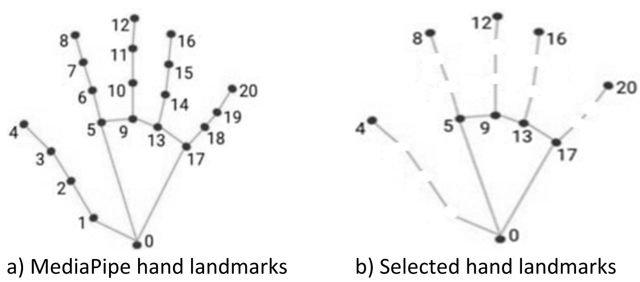


FIGURE 4. MediaPipe's hand landmarks versus the chosen hand landmarks.

aims to design and build a text-to-speech TTS module to generate high-quality speech from predefined text. We investigated state-of-the-art speech synthesis models to generate high-quality speech from the text. As a result, we choose the state-of-the-art neural TTS model FastSpeech2 [54] based on a variety of experiments. We selected FastSpeech2 because of its fast properties and support for multi-speakers. The main goal of this module is to take the text of the recognized signs from the sign language module and pronounce it to the non-deaf person. To train the FastSpeech2 model for producing the speech for only the selected 293 signs we needed to record the speech of these signs many times, but this will limit the speech synthesis to only the 293 signs. Our future goal is to cover all the 3000 signs of the Saudi sign dictionary, hence instead we opted to use KSU speech database [55] to build a speech synthesis system that can vocalize any text. We trained FastSpeech2, with the speech of selected speakers from the KSU speech database who were also on the project team and agreed to use their speaking style in the system. The trained model produced good quality speech for any text including the words of the 293 signs.

C. AVATAR MODULE (AM)

We developed the **AM** to transform the text from a normal individual into sign language, which is then executed through an Avatar. This enables individuals with hearing impairments to comprehend the spoken communication of those who can hear. To develop a Saudi sign language avatar application, it is required to make or draw a personage with local clothes, from both genders, at a medium age, as shown in **Fig. 5**. The design of the sign language Avatar passed through many steps: Firstly, we took a men and women character from IClone software [56] character creator and changed their physiques to match the Saudi men and women. The physiques include facial characteristics, such as skin, nose, eyes colors, general face shape, body size etc. Secondly, we exported only the bodies of those characters to [57], which is specialized in cloth design. In Marvelous, we designed and simulated the Arabic Thob for the man and the Hijab for the woman character. Thirdly, we exported only the clothes back to IClone character creator, and obtained the characters as shown in **Fig. 5**.

FIGURE 5. Proposed avatar characters with local clothes.

V. PROPOSED SDCS EXPERIMENTATION AND INTEGRATION

In this section, we will illustrate the performance of the proposed SDCS system, therefore, first, we will discuss the integrations of all modules (SRM, SRSM, AM), then each one individually. As mentioned, we have three different modules (SRM, SRSM, and AM) developed with different programming languages and applications, AM was developed using IClone Pro, 3DXchange, and Unity. In contrast, SRSM was developed using the KALDI toolbox, and SRM was developed using Python.

The heterogeneity of programming languages and tools posed integration challenges related to data exchange, communication protocols, and synchronization. Coordinating the seamless interaction between these modules required careful planning and the development of interfaces and connectors to ensure that data flows smoothly among them. Additionally, addressing compatibility issues and optimizing the performance of the integrated system were essential steps in overcoming these integration challenges.

Hence, the integration of all components and the exchange of data among them were achieved through the utilization of the Robot Operating System (ROS). ROS stands as an open-source, meta-operating system designed for robots, furnishing the essential functions akin to those of an operating system. These functions encompass hardware abstraction, control over low-level devices, and the realization of frequently employed features, alongside facilitating message-based communication between processes. A ROS setup consists of multiple autonomous nodes, wherein communication among them follows the publish/subscribe messaging paradigm, exemplified in **Fig. 6**. These messages have the potential to be utilized by numerous other nodes. It is noteworthy that the nodes within the ROS framework are not restricted to a common system (computers) or even a consistent architecture. For instance, one could have an Arduino disseminating messages while a laptop subscribes to them, or even involve an Android phone in the process. This inherent flexibility of ROS renders it exceptionally versatile and amenable to the diverse requirements of users, and it is precisely this adaptability that led us to select ROS as the integration platform for our modules.

FIGURE 6. ROS structure.

For the SRSM, we need a trigger to start and stop the module when it is needed and also, we need to send the result from the SRSM module to the AM module. Therefore, we create a node for SRSM module that contains a subscriber to topic called "start_stop_REC" and another node for the Speaker module that has a publisher to the same topic. In this way the AM module can send trigger signal to the SRSM module to start or stop the recording of audio signal from the microphone. And in the other way the SRSM node has a publisher to a topic called "text_from_speech" to publish the result of the speech recognition process at the end of the audio recording, in the other side the AM will subscribe to this topic to get the text result from the SRSM. **Fig. 7** shows the communication structure of the two modules.

In the AM module a graphical record button will be created and linked to the "start_stop_REC" topic as shown in **Fig. 8**, so when the user presses the button a "Start" message will be sent to this topic and when it releases it a "Stop" message will be sent to the same topic.

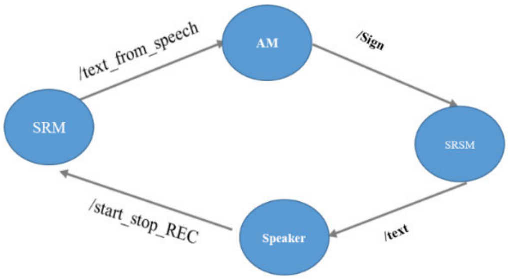


FIGURE 7. Communication between modules.

FIGURE 8. Start speech recognition button.

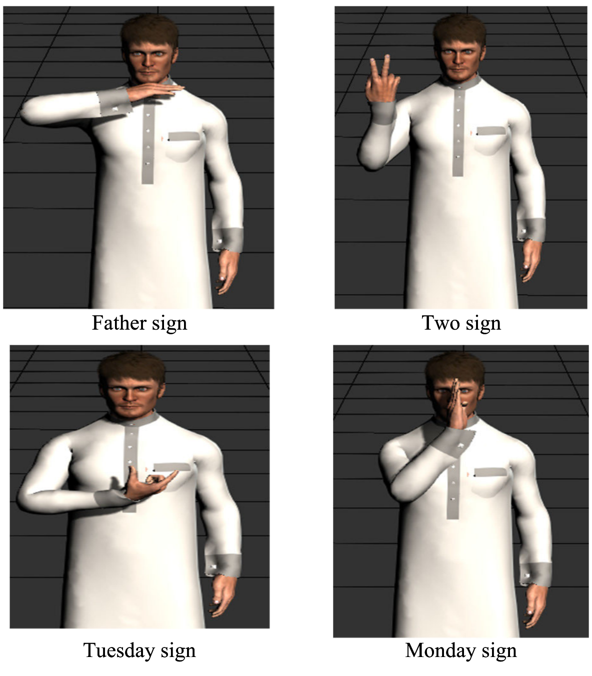
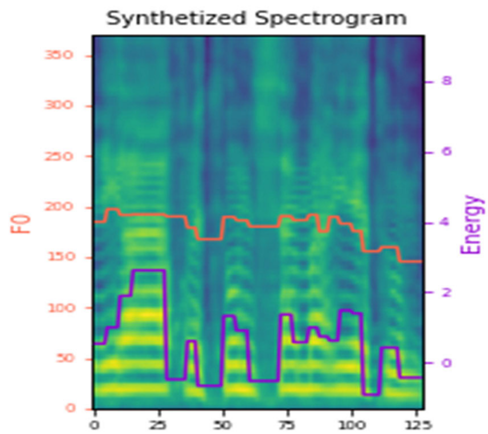
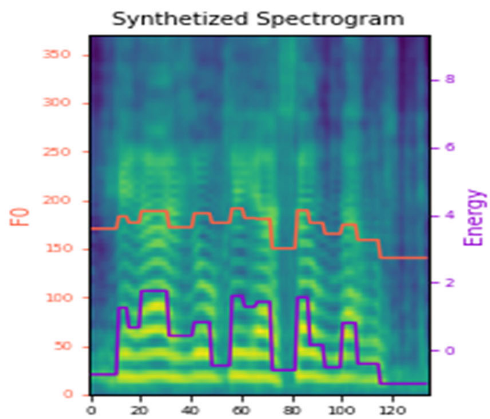


FIGURE 9. Avatar sample signs.

In the other side, the SRSM module has a callback function linked to the "start_stop_REC" topic, so when the "Start" message is received the speech recognition module will start recording audio from the microphone, then when a "Stop" message is received the speech recognition module stop the recording from the microphone and start the recognition process on the recorded audio file, and when the it get the result of the speech recognition the result it will be sent to the "text_from_speech" topic.

TABLE 4. Examples of the generated spectrograms.

WORD & SYNTHESIZED SPECTROGRAM
إعاقة سمعية

جهاز قياس الضغط


In the other side the AM split the text received into list of words, then starts looking for most similar synonym in the Sign language database using DTW (Dynamic Time Warping) algorithm, if it did find a similar synonym the controller will send the corresponding motion of each word to the avatar to perform it, else if it did not the controller will split the word that not found into letters and send the corresponding motion of each letter to the avatar so the word will be performed as sequence of letters. Samples view of the developed Avatar signs are presented in **Fig. 9**.

In *Table 4*, the synthesized spectrograms of the proposed SRSM for four signs from the project 293 signs are shown, where we can see that FastSpeech2 can generate high-quality spectrograms. After generating the spectrograms by FastSpeech2 we used the vocoder HiFi-GAN to generate the speech using the spectrograms.

TABLE 5. Evaluation results of the 3DGCN on the proposed dataset.

Accuracy (Avg.)	Epochs	Size of batch	Validation	Size of Training	Num. of classes
97.25	200	32	5,860	28,021	293

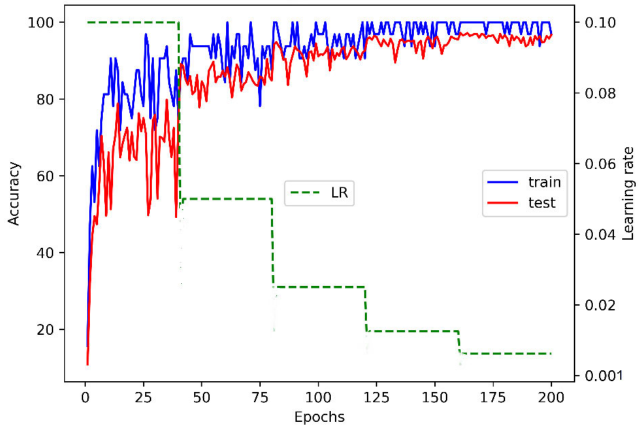


FIGURE 10. The performance behavior of the proposed 3DGCN architecture on our proposed KSU-SSL dataset.

TABLE 6. Properties of references datasets.

Dataset	classes	Training samples	Validation samples
Our (KSU-ArSL)	293	84,063	17,580
Jester	27	118558	14786
AUTSL	226	28142	4418
SLA-64	64	2560	640
ASLLVD	2745	7798	1950
ASLLVD-20	20	85	42

To train FastSpeech2 for developing the Arabic synthesizer, the PyTorch implementation of the GitHub repository [54] is used. We followed the same provided training configuration. In particular, we used multi-speaker mode, 16 batch size, 600K training steps, and HiFi-GAN vocoder. Selected native speakers from the KSU speech database are used to train the TTS model; the sample rate of the audio files is 22050 Hz. Samples of synthesized spectrograms for some words from the 293 signs that do not exist in the text of the training are shown in *Table 4*.

As depicted in Table 5, the 3DGCN framework introduced in the context of the SRM yielded a remarkable mean accuracy of 97.25% when applied to the proposed dataset. The training process employed a batch size of 32, drawing from a training dataset comprising 28,021 samples. To validate the training progression, an independent set of 5,860 samples was employed. The model underwent 200 epochs of training in total.

Fig. 10 shows the gradual adjustment of the architecture to the ideal hyperparameters throughout the training process on

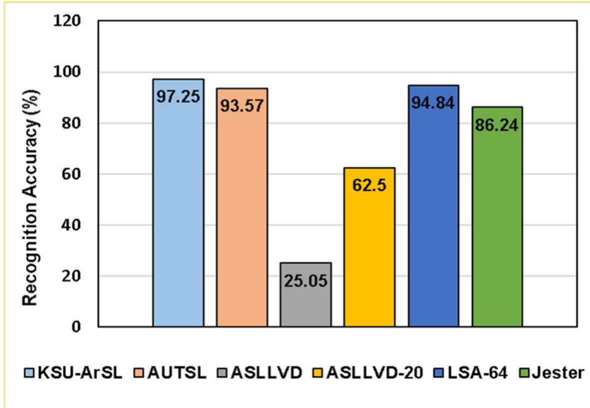


FIGURE 11. Comparison of 3DGCN accuracy with other reference datasets.

the KSU-SSL dataset. Additionally, it shows how the learning rate consistently decreases, indicating the architecture's smooth adaptation to the dataset.

Several other datasets are used for evaluation, the AUTSL dataset [58], the LSA-64 [59], the ASLLV [60], and Jester [61]. The properties of these datasets are shown in Table 6

Fig. 11 compared the accuracy of the proposed 3DGCN on different datasets.

VI. CONCLUSION

In conclusion, this study presented a complete solution for two-way communication of deaf individuals. The proposed system consists of three modules; SRM that recognizes the signs of deaf individual; the SRSM module that processes the speech of a non-deaf individual and convert it to text, and an Avatar module (AM) to generate and perform the corresponding sign of the non-deaf speech using Saudi local clothes, from both genders, at a medium age., which were integrated into the sign translation companion system called deaf companion System (SDCS). The proposed SDCS system performs 293 Saudi signs that are recommended by SAHI from 10 domains (healthcare, common, alphabets, verbs, pronouns and adverbs, numbers, days, kings, family, and regions). Overall, the proposed SDCS system and the KSU-SSL database make significant strides in improving the communication and integration of deaf individuals into society, allowing them to transition from marginalized elements to active contributors within mainstream society. In the future, we are planning to extend the number of signs to cover all 3000 signs that are included in the Saud sign dictionary. And integrate the proposed system with a portable robot.

REFERENCES

[1] World Health Organization. *Disability*. Accessed: Oct. 30, 2023. [Online]. Available: http://www.who.int/disabilities/infographic/en/

[2] M. Marschark, H. G. Lang, and J. A. Albertini, *Educating Deaf Students: From Research to Practice*. New York, NY, USA: Oxford Univ. Press, 2001.

[3] H. Knoors, G. Tang, and M. Marschark, *Bilingualism and Bilingual Deaf Education*. USA: Oxford Univ. Press, 2014, pp. 1–20.

[4] G. P. Berent and R. R. Kelly, "The efficacy of visual input enhancement in teaching deaf learners of L2 English," in *Understanding Second Language Process*, vol. 25. U.K.: Multilingual Matters, 2007, p. 80.

[5] World Health Organization. (Jan. 15, 2017). *Deafness and Hearing Loss*. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs300/en/

[6] A. Al-Nafjan, B. Al-Arifi, and A. Al-Wabil, "Design and development of an educational Arabic sign language mobile application: Collective impact with Tawasol," in *Proc. Int. Conf. Universal Access Human-Comput. Interact.*, 2015, pp. 319–326.

[7] GAF Statistics. (Jan. 15, 2017). *Demography Survey*. [Online]. Available: https://www.stats.gov.sa/sites/default/files/disability_survey_2017_ar.pdf

[8] T. Shanableh and K. Assaleh, "Telescopic vector composition and polar accumulated motion residuals for feature extraction in Arabic sign language recognition," *EURASIP J. Image Video Process.*, vol. 2007, Oct. 2007, Art. no. 087929.

[9] M. Mohandes, S. I. Quadri, and M. Deriche, "Arabic sign language recognition an image-based approach," in *Proc. 21st Int. Conf. Adv. Inf. Netw. Appl. Workshops (AINAW)*, May 2007, pp. 272–276.

[10] S. M. Shohieb, H. K. Elminir, and A. M. Riad, "SignsWorld atlas; a benchmark Arabic sign language database," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 27, no. 1, pp. 68–76, Jan. 2015.

[11] M. ElBadawy, A. S. Elons, H. Sheded, and M. F. Tolba, "A proposed hybrid sensor architecture for Arabic sign language recognition," in *Intelligent Systems*. Cham, Switzerland: Springer, 2015, pp. 721–730.

[12] G. Latif, N. Mohammad, J. Alghazo, R. AlKhalaf, and R. AlKhalaf, "ArASL: Arabic alphabets sign language dataset," *Data Brief*, vol. 23, Apr. 2019, Art. no. 103777.

[13] O. Al-Jarrah and A. Halawani, "Recognition of gestures in Arabic sign language using neuro-fuzzy systems," *Artif. Intell.*, vol. 133, nos. 1–2, pp. 117–138, Dec. 2001.

[14] N. R. Albelwi and Y. M. Alginahi, "Real-time Arabic Sign Language (ArSL) recognition," in *Proc. Int. Conf. Commun. Inf. Technol.*, 2012, pp. 497–501.

[15] A. SamirElons, M. Abull-ela, and M. F. Tolba, "Pulse-coupled neural network feature generation model for Arabic sign language recognition," *IET Image Process.*, vol. 7, no. 9, pp. 829–836, Dec. 2013.

[16] F. Guesmi, T. Bouchrika, O. Jemai, M. Zaied, and C. Ben Amar, "Arabic sign language recognition system based on wavelet networks," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2016, pp. 3561–3566.

[17] K. Assaleh, T. Shanableh, M. Fanaswala, H. Bajaj, and F. Amin, "Vision-based system for continuous Arabic sign language recognition in user dependent mode," in *Proc. 5th Int. Symp. Mechatronics Appl.*, May 2008, pp. 1–5.

[18] M. F. Tolba, A. Samir, and M. Abul-Ela, "A proposed graph matching technique for Arabic sign language continuous sentences recognition," in *Proc. 8th Int. Conf. Informat. Syst. (INFOS)*, May 2012, pp. 14–20.

[19] M. A. Bencherif, M. Algabri, M. A. Mekhtiche, M. Faisal, M. Alsulaiman, H. Mathkour, M. Al-Hammadi, and H. Ghaleb, "Arabic sign language recognition system using 2D hands and body skeleton data," *IEEE Access*, vol. 9, pp. 59612–59627, 2021.

[20] J. Branson and D. Miller, "'Language': Linguistic imperialism, sign languages and linguistic anthropology," in *Disinventing and Reconstituting Languages*. U.K.: Multilingual Matters, 2007, p. 80. 2007, pp. 116–134.

[21] A. S. Al-Shamayleh, R. Ahmad, N. Jomhari, and M. A. M. Abushariah, "Automatic Arabic sign language recognition: A review, taxonomy, open challenges, research roadmap and future directions," *Malaysian J. Comput. Sci.*, vol. 33, no. 4, pp. 306–343, Oct. 2020.

[22] H. Alawad, *Teachers' Beliefs About the Use of Fingerspelling in Deaf Education Classrooms in Saudi Arabia: A Qualitative Case Study*. Beaumont, TX, USA: Lamar Univ., 2020.

[23] F. Albogamy, M. Faisal, M. Arafah, and H. ElGibreen, "COVID-19 symptoms periods detection using transfer-learning techniques," *Intell. Autom. Soft Comput.*, vol. 32, no. 3, pp. 1921–1937, 2022.

[24] M. Faisal, F. Albogamy, H. ElGibreen, M. Algabri, S. Ahad M. Alvi, and M. Alsulaiman, "COVID-19 diagnosis using transfer-learning techniques," *Intell. Autom. Soft Comput.*, vol. 29, no. 3, pp. 649–667, 2021.

[25] M. Faisal, H. ElGibreen, N. Alafif, and C. Joumaa, "Reducing children's obesity in the age of telehealth and AI/IoT technologies in Gulf countries," *Systems*, vol. 10, no. 6, p. 241, Dec. 2022.

[26] M. Al-Hammadi, M. A. Bencherif, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, W. Abdul, Y. A. Alohali, T. S. Alrayes, H. Mathkour, M. Faisal, M. Algabri, H. Altaheri, T. Alfakih, and H. Ghaleb, "Spatial attention-based 3D graph convolutional neural network for sign language recognition," *Sensors*, vol. 22, no. 12, p. 4558, Jun. 2022.

[27] H. Altaheri, M. Alsulaiman, M. Faisal, and G. Muhammed, 2019, "Date fruit dataset for automated harvesting and visual yield estimation," *IEEE DataPort*, doi: 10.21227/x46j-sk98.

[28] M. Al Sulaiman, A. M. Moussa, S. Abdou, H. Elgibreen, M. Faisal, and M. Rashwan, "Semantic textual similarity for modern standard and dialectal Arabic using transfer learning," *PLoS One*, vol. 17, no. 8, Aug. 2022, Art. no. e0272991.

[29] M. Faisal, K. Al-Mutib, R. Hedjar, H. Mathkour, M. Alsulaiman, and E. Mattar, "Behavior based mobile for mobile robots navigation and obstacle avoidance," *Int. J. Comput. Commun.*, vol. 8, pp. 33–40, Jan. 2014.

[30] K. Al-Muteb, M. Faisal, M. Emaduddin, M. Arafah, M. Alsulaiman, M. Mekhtiche, R. Hedjar, H. Mathkoor, M. Algabri, and M. A. Bencherif, "An autonomous stereovision-based navigation system (ASNS) for mobile robots," *Intell. Service Robot.*, vol. 9, no. 3, pp. 187–205, Jul. 2016.

[31] E. Rajalakshmi, R. Elakkiya, V. Subramaniyaswamy, L. P. Alexey, G. Mikhail, M. Bakaev, K. Kotecha, L. A. Gabralla, and A. Abraham, "Multi-semantic discriminative feature learning for sign gesture recognition using hybrid deep neural architecture," *IEEE Access*, vol. 11, pp. 2226–2238, 2023.

[32] E. Rajalakshmi, R. Elakkiya, A. L. Prikhodko, M. G. Grif, M. A. Bakaev, J. R. Saini, K. Kotecha, and V. Subramaniyaswamy, "Static and dynamic isolated Indian and Russian sign language recognition with spatial and temporal feature detection using hybrid neural network," *ACM Trans. Asian Low-Resource Lang. Inf. Process.*, vol. 22, no. 1, pp. 1–23, Jan. 2023.

[33] B. Natarajan, E. Rajalakshmi, R. Elakkiya, K. Kotecha, A. Abraham, L. A. Gabralla, and V. Subramaniyaswamy, "Development of an end-to-end deep learning framework for sign language recognition, translation, and video generation," *IEEE Access*, vol. 10, pp. 104358–104374, 2022.

[34] A. Ali, Y. Zhang, P. Cardinal, N. Dahak, S. Vogel, and J. Glass, "A complete KALDI recipe for building Arabic speech recognition systems," in *Proc. IEEE Spoken Lang. Technol. Workshop (SLT)*, Dec. 2014, pp. 525–529.

[35] W. Abdul, M. Alsulaiman, S. U. Amin, M. Faisal, G. Muhammad, F. R. Albogamy, M. A. Bencherif, and H. Ghaleb, "Intelligent real-time Arabic sign language classification using attention-based inception and BiLSTM," *Comput. Electr. Eng.*, vol. 95, Oct. 2021, Art. no. 107395.

[36] H. L. M. Glenn, S. Strassel, and K. Maeda. (2016). *GALE Phase 3 Arabic Broadcast News Transcripts—Part 1*. [Online]. Available: https://catalog.ldc.upenn.edu/LDC2016T17

[37] N. Zerari, S. Abdelhamid, H. Bouzgou, and C. Raymond, "Bidirectional deep architecture for Arabic speech recognition," *Open Comput. Sci.*, vol. 9, no. 1, pp. 92–102, Jan. 2019.

[38] B. Dendani, H. Bahi, and T. Sari, "Speech enhancement based on deep autoencoder for remote Arabic speech recognition," in *Proc. 9th Int. Conf. Image Signal Process.*, Marrakesh, Morocco, 2020, pp. 221–229.

[39] Y. Yang. (2021). *Kaldi Speech Recognition Toolkit*. [Online]. Available: https://github.com/kaldi-asr/kaldi

[40] A. Hannun, C. Case, J. Casper, B. Catanzaro, G. Diamos, E. Elsen, R. Prenger, S. Satheesh, S. Sengupta, A. Coates, and A. Y. Ng, "Deep speech: Scaling up end-to-end speech recognition," 2014, *arXiv:1412.5567*.

[41] V. Pratap, A. Hannun, Q. Xu, J. Cai, J. Kahn, G. Synnaeve, V. Liptchinsky, and R. Collobert, "Wav2letter++: The fastest open-source speech recognition system," 2018, *arXiv:1812.07625*.

[42] M. Ravanelli, T. Parcollet, and Y. Bengio, "The PyTorch–Kaldi speech recognition toolkit," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 6465–6469.

[43] O. Kuchaiev, B. Ginsburg, I. Gitman, V. Lavrukhin, J. Li, H. Nguyen, C. Case, and P. Micikevicius, "Mixed-precision training for NLP and speech recognition with OpenSeq2Seq," 2018, *arXiv:1805.10387*.

[44] H. Inaguma, S. Kiyono, K. Duh, S. Karita, N. E. Y. Soplin, T. Hayashi, and S. Watanabe, "ESPnet-ST: All-in-one speech translation toolkit," 2020, *arXiv:2004.10234*.

[45] A. H. Aliwy and A. A. Alethary, "Development of Arabic sign language dictionary using 3D avatar technologies," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 21, no. 1, pp. 609–616, Jan. 2021.

[46] S. M. Halawani and A. Zaitun, "An avatar based translation system from Arabic speech to Arabic sign language for deaf people," *Int. J. Inf. Sci. Educ.*, vol. 2, no. 1, pp. 13–20, 2012.

[47] M. M. El-Gayyar, A. S. Ibrahim, and M. E. Wahed, "Translation from Arabic speech to Arabic sign language based on cloud computing," *Egyptian Informat. J.*, vol. 17, no. 3, pp. 295–303, Nov. 2016.

[48] M. Brour and A. Benabbou, "ATLASLang MTS 1: Arabic text language into Arabic sign language machine translation system," *Proc. Comput. Sci.*, vol. 148, pp. 236–245, Jan. 2019.

[49] Y. Regragui, L. Abouenour, F. Krieche, K. Bouzoubaa, and P. Rosso, "Arabic WordNet: New content and new applications," in *Proc. 8th Global WordNet Conf. (GWC)*, 2016, pp. 333–341.

[50] A. Boudlal, A. Lakhouaja, A. Mazroui, A. Meziane, M. Bebah, and M. Shoul, "Alkhalil Morpho Sys[1]: A morphosyntactic analysis system for Arabic texts," in *Proc. Int. Arab Conf. Inf. Technol.*, 2010, pp. 1–6.

[51] M. A. Alobaidy and S. K. Ebraheem, "Application for Iraqi sign language translation on Android system," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 5, p. 5227, Oct. 2020.

[52] M. Alsulaiman, M. Faisal, M. Mekhtiche, M. Bencherif, T. Alrayes, G. Muhammad, H. Mathkour, W. Abdul, Y. Alohali, M. Alqahtani, H. Al-Habib, H. Alhalafi, M. Algabri, M. Al-hammadi, H. Altaheri, and T. Alfakih, "Facilitating the communication with deaf people: Building a largest Saudi sign language dataset," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 35, no. 8, Sep. 2023, Art. no. 101642.

[53] C. Lugaresi, J. Tang, H. Nash, C. McClanahan, E. Uboweja, M. Hays, F. Zhang, C.-L. Chang, M. Yong, J. Lee, W.-T. Chang, W. Hua, M. Georg, and M. Grundmann, "MediaPipe: A framework for perceiving and processing reality," in *Proc. 3rd Workshop Comput. Vis. AR/VR IEEE Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 1–4.

[54] Y. Ren, C. Hu, X. Tan, T. Qin, S. Zhao, Z. Zhao, and T.-Y. Liu, "FastSpeech 2: Fast and high-quality end-to-end text to speech," 2020, *arXiv:2006.04558*.

[55] M. M. Alsulaiman, G. Muhammd, M. A. Bencherif, A. Mahmood, and Z. Ali, "KSU rich Arabic speech database," *J. Inf.*, vol. 16, no. 6, pp. 4231–4253, 2013.

[56] M. McCallum, *iClone 4.31 3D Animation Beginner's Guide*. Birmingham, U.K.: Packt, 2011.

[57] M Company. (Jun. 14, 2023). *Marvelous Designer*. [Online]. Available: https://marvelousdesigner.com/

[58] O. M. Sincan and H. Y. Keles, "AUTSL: A large scale multi-modal Turkish sign language dataset and baseline methods," *IEEE Access*, vol. 8, pp. 181340–181355, 2020.

[59] F. Ronchetti, F. Quiroga, C. A. Estrebou, L. C. Lanzarini, and A. Rosete, "LSA64: An Argentinian sign language dataset," in *Proc. 33rd Congreso Argentino de Ciencias de la Computación (CACIC)*, 2016, pp. 794–803.

[60] C. Neidle, A. Thangali, and S. Sclaroff, "Challenges in development of the American Sign Language Lexicon Video Dataset (ASLLVD) corpus," in *Proc. 5th Workshop Represent. Process. Sign Lang., Interact. Between Corpus Lexicon*, 2012, pp. 1–8.

[61] J. Materzynska, G. Berger, I. Bax, and R. Memisevic, "The jester dataset: A large-scale video dataset of human gestures," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. Workshop (ICCVW)*, Oct. 2019, pp. 2874–2882.

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