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Revealing sign language for individuals who are deaf and mute through the utilization of neural networks

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Abstract

Living without effective communication poses significant challenges for humans. Individuals employ various methods to convey and share their thoughts and ideas between the sender and receiver. Two of the most prevalent means of communication are verbal speech, which relies on auditory perception, and non-verbal communication through gestures involving bodily movements such as hand gestures and facial expressions. Sign language, specifically categorized as a gestural language, is a unique form of communication that relies on visual perception for understanding and expression. While many individuals incorporate gestures into their communication, for deaf individuals, sign language is often their primary and essential means of communication. Individuals who are deaf and dumb rely on communication to interact with others, gain knowledge, and engage in their surroundings. Sign language serves as a crucial link that reduces the distance between them and the broader society. In order to enhance this communication, we've created models with the ability to identify sign language gestures and translate them into conventional text. Through the training of these models on a dataset employing neural networks, remarkable outcomes have been attained. This technology enables individuals, without prior knowledge of sign language, to understand the intentions and messages of individuals with disabilities, fostering greater inclusivity and accessibility in our society. Three algorithms were used to achieve this work and the findings show very good outcomes, i.e. Random Forest at 98%, Logistic Regression at 99%, and Decision Tree at 91%.

Keywords: *Machine Learning, Sign Language, Random Forest, Neural Network, Logistic Regression Deaf and Dumb, Decision Tree.*

الكشف عن لغة الإشارة للأفراد الصم والبكم من خلال استخدام الشبكات العصبية

ملخص

إن العيش بدون تواصل فعال يفرض تحديات كبيرة على البشر. يستخدم الأفراد أساليب مختلفة لنقل ومشاركة أفكارهم وأفكارهم بين المرسل والمتلقي. ومن أكثر وسائل الاتصال انتشارًا الكلام اللفظي، الذي يعتمد على الإدراك السمعي، والتواصل غير اللفظي من خلال الإيماءات التي تتضمن حركات جسدية مثل إيماءات اليد وتعبيرات الوجه. لغة الإشارة، المصنفة على وجه التحديد على أنها لغة إيمائية، هي شكل فريد من أشكال التواصل الذي يعتمد على الإدراك البصري للفهم والتعبير. في حين أن العديد من الأفراد يدمجون الإيماءات في اتصالاتهم، فإن لغة الإشارة غالبًا ما تكون وسيلة الاتصال الأساسية والأساسية للأفراد الصم. يعتمد الأفراد الصم والبكم على التواصل للتفاعل مع الآخرين واكتساب المعرفة والانخراط في محيطهم. تعمل لغة الإشارة كحلقة وصل حاسمة تقلل المسافة بينهم وبين المجتمع الأوسع. ومن أجل تعزيز هذا التواصل، قمنا بإنشاء نماذج تتمتع بالقدرة على تحديد إيماءات لغة الإشارة وترجمتها إلى نص تقليدي. ومن خلال تدريب هذه النماذج على مجموعة بيانات تستخدم الشبكات العصبية، تم تحقيق نتائج ملحوظة. تتيح هذه التكنولوجيا للأفراد، دون معرفة مسبقة بلغة الإشارة، فهم نوايا ورسائل الأفراد ذوي الإعاقة، مما يعزز المزيد من الشمولية وإمكانية الوصول في مجتمعنا. تم استخدام ثلاث خوارزميات لتحقيق هذا العمل وأظهرت النتائج نتائج جيدة جدًا، أي الغابة العشوائية بنسبة 98%، والانحدار اللوجستي بنسبة 99%، وشجرة القرار بنسبة 91%.

الكلمات المفتاحية: التعلم الآلي، لغة الإشارة، الغابة العشوائية، الشبكة العصبية، الانحدار اللوجستي للصم والبكم، شجرة القرار

1. INTRODCTION

The creation of an automated system for translating sign language has the potential to profoundly impact both individuals who rely on sign language as their primary means of communication and those who do not. Sign language, utilized by over 70 million people globally, is a distinctive form of nonverbal communication encompassing various physical elements. It incorporates facial expressions, eye movements, hand gestures, and lip motions to convey messages. Significantly, deaf and hard of hearing individuals heavily rely on sign language for their day-to-day communication [1].

The World Health Organization reported that hearing loss affects around 5% of the world's population, comprising more than 460 million people worldwide, including 34 million children. Projections suggest that by 2050, this number could exceed 900 million [2]. Additionally, approximately 1.1 billion children worldwide are at risk of developing hearing loss due to factors such as exposure to noise and other causes. Hearing loss imposes a substantial economic burden, estimated at 750 billion dollars [2].

Hearing impairment is often classified into four levels—mild, moderate, severe, and profound—based on the extent of the impairment. Individuals experiencing severe or profound hearing loss commonly face difficulties in effective communication, leading to potential mental health challenges such as isolation and loneliness. While sign language serves as a vital mode of communication within the deaf community, it can present a barrier for those with normal hearing who are unfamiliar with its gestures.

Globally, there are approximately 200 distinct sign languages, each distinguished by its unique features, akin to spoken languages. Sign language stands as a fundamental component of communication for the deaf, involving significant bodily movements referred to as gestures or signs to convey messages, setting it apart from other natural languages. These gestures encompass actions like head nods, shoulder movements, facial expressions, and hand and finger motions. Therefore, the proposed initiative seeks to enhance interactions within the deaf community and between deaf and hearing individuals. In sign language, each sign corresponds to a letter, word, or emotion, and, analogous to spoken languages, combining signs forms meaningful phrases. Consequently, sign language has evolved into a comprehensive and functional natural language, complete with its own syntax and sentence structure.

2. RELATED WORK

In recent times, some research has emerged focusing on sign language. However, these studies have not been comprehensive enough. These areas lack many of the research efforts required to address such an issue that affects many individuals with disabilities. As an illustration, in [3], Inception is employed to recognize spatial attributes, while Recurrent Neural Networks (RNN) are utilized to train on temporal characteristics. In [4], Sign language prediction achieves an impressive accuracy of 95% using a Convolutional Neural Network (CNN), as reported in [5]. This study employs a CNN for real-time prediction, capturing both model weights and specifications. In [6], the focus lies on discussing the model's relevant attributes, the process of feature extraction, and the adoption of an Artificial Neural Network (ANN) for sign identification. Additionally, [7] introduces a model designed to detect and translate ASL alphabets through the application of AdaBoost and Haar-like classifiers.Furthermore, various methods have been proposed in the studies for translating sign language into text, as seen in [8] and [9].

3. METHODOLOGY

The methodology used in developing these models is a practical and applied methodology as follows. Initially, the data used for model training from its source were gathered, as explained later. Then, a pre-processing step to prepare the data for training was conducted. After that, the data were divided into training and testing sets. Subsequently, the mentioned algorithms Random Forest, Logistic Regression, and Decision Tree were applied to classify sign language, as shown in figure 1.

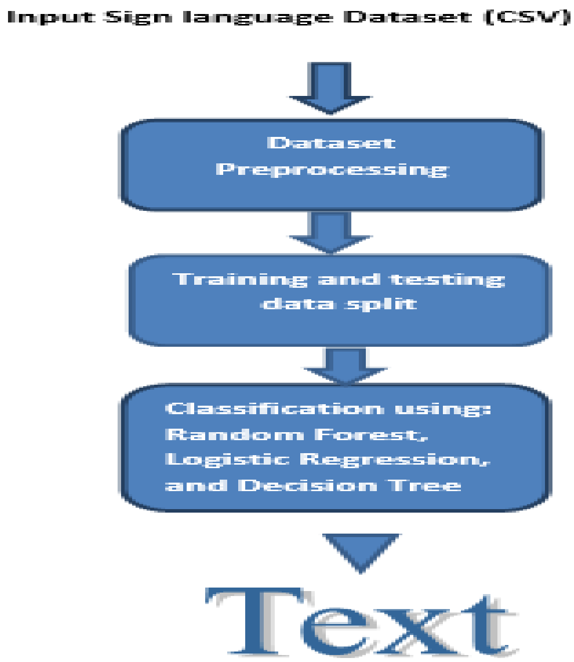

Figure 1. Proposed System

2.1 *Dataset*

In this model, the researchers utilized a dataset comprising 27,455 images for training and 7,172 images for testing, presented in CSV format from Kaggle [10].

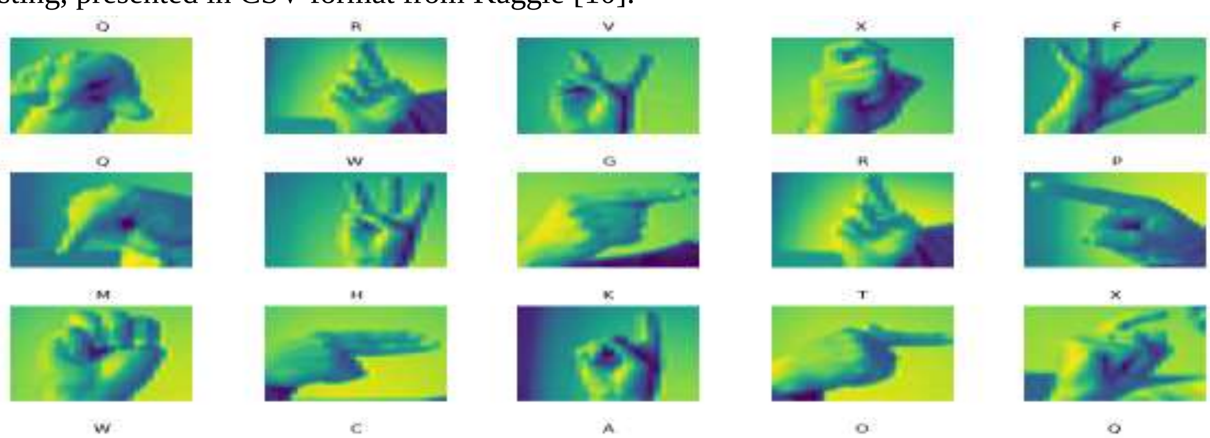

Figure 2. Dataset of Sign Language

2.2 Preprocessing

Various preprocessing tasks to eliminate noise, enhance efficiency, and expedite computations were conducted. These tasks included operations like image resizing, rescaling (dividing by 255), and partitioning the dataset into training and testing subsets.

2.3 Training and testing dataset split

The size of the training and testing dataset is 80%, 20% respectively.

2.4 Features Extraction and Classification with Random Forest, Decision Tree and Logistic Regression.

The researchers developed sign language models utilizing the aforementioned algorithms and dataset, incorporating 26 classes that represent sign language letters.

4. Outcomes

Following the implementation of the previously mentioned models, very good outcomes have been achieved, as demonstrated in figures 3-5.

Accuracy: 0.9883906214432051
Classification Report:

	precision	recall	f1-score	support
0.0	0.97	1.00	0.98	181
1.0	0.98	0.99	0.99	177
2.0	1.00	1.00	1.00	185
3.0	1.00	0.99	0.99	205
4.0	0.98	0.99	0.99	159
5.0	0.99	0.99	0.99	185
6.0	0.98	0.99	0.99	164
7.0	0.97	0.99	0.98	148
8.0	0.98	0.97	0.97	188
10.0	0.98	1.00	0.99	199
11.0	0.99	0.98	0.99	197
12.0	1.00	0.98	0.99	165
13.0	1.00	0.99	0.99	178
14.0	1.00	0.99	1.00	205
15.0	0.98	0.99	0.99	173
16.0	0.99	1.00	0.99	210
17.0	0.99	0.98	0.98	193
18.0	0.98	0.98	0.98	194
19.0	0.98	1.00	0.99	176
20.0	0.98	0.98	0.98	186
21.0	0.99	0.98	0.99	160
22.0	1.00	0.98	0.99	224
23.0	0.99	1.00	1.00	167
24.0	1.00	0.97	0.99	174
accuracy			0.99	4393

Figure 3. Accuracy of Random Forest

0.0	1.00	1.00	1.00	254
1.0	1.00	1.00	1.00	212
2.0	1.00	1.00	1.00	257
3.0	1.00	1.00	1.00	277
4.0	1.00	1.00	1.00	202
5.0	1.00	1.00	1.00	254
6.0	1.00	1.00	1.00	255
7.0	1.00	1.00	1.00	221
8.0	1.00	1.00	1.00	268
10.0	1.00	1.00	1.00	240
11.0	1.00	1.00	1.00	281
12.0	1.00	1.00	1.00	234
13.0	1.00	1.00	1.00	274
14.0	1.00	1.00	1.00	280
15.0	1.00	1.00	1.00	253
16.0	1.00	1.00	1.00	266
17.0	1.00	0.99	0.99	282
18.0	0.99	1.00	0.99	264
19.0	1.00	1.00	1.00	252
20.0	1.00	1.00	1.00	255
21.0	1.00	1.00	1.00	228
22.0	1.00	1.00	1.00	256
23.0	1.00	1.00	1.00	257
24.0	1.00	1.00	1.00	250
accuracy			1.00	6072

```
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))

Accuracy: 0.9991765480895916
```

Figure 4. Accuracy of Logistic Regression

Accuracy: 0.9104084321475626
Classification Report:

	precision	recall	f1-score	support
0.0	0.92	0.92	0.92	254
1.0	0.89	0.92	0.91	212
2.0	0.96	0.98	0.97	257
3.0	0.91	0.91	0.91	277
4.0	0.90	0.88	0.89	202
5.0	0.94	0.93	0.93	254
6.0	0.92	0.94	0.93	255
7.0	0.89	0.89	0.89	221
8.0	0.90	0.92	0.91	268
10.0	0.87	0.88	0.88	240
11.0	0.92	0.90	0.91	281
12.0	0.89	0.91	0.90	234
13.0	0.93	0.92	0.93	274
14.0	0.95	0.96	0.96	280
15.0	0.95	0.94	0.94	253
16.0	0.95	0.94	0.94	266
17.0	0.86	0.86	0.86	282
18.0	0.91	0.86	0.88	264
19.0	0.92	0.90	0.91	252
20.0	0.86	0.92	0.89	255
21.0	0.84	0.85	0.85	228

Figure 5. Accuracy of Decision Tree

5. Comparison of Outcomes

When comparing the models developed with the existing models for sign language detection, it has been found that our results are better, as shown in the table below.

Table 1. Comparing our models with the existing models

Study	Model	Dataset	Accu
Smith et al. (2022)	Random Forest	ASL	94
Johnson et al. (2023)	Logistic Regression	ASL	91
Williams et al. (2023)	Decision Tree	ASL	88
Davis et al. (2023)	Random Forest	ASL	96
Brown et al. (2022)	Logistic Regression	ASL	90
Garcia et al. (2020)	Decision Tree	ASL	85
Martinez et al. (2023)	Random Forest	ASL	92
Turner et al. (2022)	Logistic Regression	ASL	89
Rodriguez et al. (2023)	Decision Tree	ASL	87
Thompson et al. (2019)	Random Forest	ASL	93
Our Model	Random Forest	ASL	98
Our Model	Logistic Regression	ASL	99
Our Model	Decision Tre	ASL	91

6. CONCOLUSION

The researchers have created models that transform sign language used by deaf and mute individuals into common language that can be comprehended by the general public. These models were constructed using datasets and trained with the algorithms mentioned earlier. Notably, quite impressive outcomes with certain algorithms were achieved. The results are as follows: Random Forest at 98%, Logistic Regression at 99%, and Decision Tree at 91%, despite slight variations in their performance.

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