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Classifiers and Image Processing to Identify Sign Language Phonemes

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ABSTRACT

One of the most visible symptoms of autism spectrum disorder is difficulty in speech and language. Difficulties in speech and language are generally very different for each child with autism spectrum disorder. Although some children with autism spectrum disorder can speak fluently, others will not be able to speak normally or will be even nonverbal. In all cases, parents try to communicate with, and understand their children's needs, desires, and emotions. If a child with autism spectrum disorder cannot speak out loud, it is harder to communicate with him/her but there are other non-vocal methods for communication. In this paper, the benefits of teaching American sign language to children with autism spectrum disorder and the difficulties that families and children will experience while doing this are presented. In addition, technological solutions to these difficulties are given. In parallel with advancements in technology, novel solutions to understand and use sign language have been proposed and these solutions are supposed to help parents who cannot understand sign language. Such solutions typically rely on image processing methods and classification algorithms to recognise sign language. Therefore, in this paper, the performance of various classification algorithms used to classify American Sign Language phonemes is compared. As the results show, when combined with image processing methods, classification algorithms can be used in various technological solutions aiming at helping to identify sign language phonemes.

Keywords: Autism spectrum disorder; Classifiers; Image processing; Machine learning; Sign language

İşaret Dili Fonemlerini Belirlemek İçin Sınıflandırıcılar ve Görüntü İşleme

ÖZ

Otizm spektrum bozukluğunun en gözle görülür semptomlarından biri konuşma ve dil güçlüğüdür. Otizm spektrum bozukluğu olan her çocuk için konuşma ve dildeki zorluklar genellikle çok farklıdır. Otizm spektrum bozukluğu olan bazı çocuklar akıcı bir şekilde konuşabilse de, diğerleri normal konuşamayacak veya sözsüz bile konuşabilecektir. Her durumda ebeveynler çocuklarının ihtiyaçları, arzuları ve duygularıyla iletişim kurmaya ve onları anlamaya çalışır. Otizm spektrum bozukluğu olan bir çocuk yüksek sesle konuşamıyorsa onunla iletişim kurmak daha zordur ancak ses dışı iletişim yöntemleri de vardır. Bu makalede, otizm spektrum bozukluğu olan çocuklara Amerikan işaret dili öğretmenin faydaları ve ailelerin ve çocukların bunu yaparken karşılaşacakları zorluklar sunulmaktadır. Ayrıca, bu zorluklara yönelik teknolojik çözümler verilmektedir. Teknolojinin ilerlemesine paralel olarak işaret dilini anlamak ve kullanmak için yeni çözümler öneriliyor ve bu çözümlerin işaret dilini anlayamayan ebeveynlere yardımcı olması bekleniyor. Bu tür çözümler genellikle işaret dilini tanımak için görüntü işleme yöntemlerine ve sınıflandırma algoritmalarına dayanır. Bu nedenle bu makalede Amerikan İşaret Dili ses birimlerini sınıflandırmak için kullanılan çeşitli sınıflandırma algoritmalarının performansı karşılaştırılmıştır.

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Sonuçların gösterdiği gibi, sınıflandırma algoritmaları görüntü işleme yöntemleriyle birleştirildiğinde işaret dili ses birimlerinin belirlenmesine yardımcı olmayı amaçlayan çeşitli teknolojik çözümlerde kullanılabilir.

Anahtar Kelimeler: Otizm spektrum bozukluğu; Sınıflandırıcılar; Görüntü işleme; Makine öğrenmesi; İşaret dili

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1. INTRODUCTION

If a child with autism spectrum disorder (ASD) has difficulty in speech, intervention services should be provided as soon as possible in order to give the child the best possible chance of achieving functional communication later on. Therefore, the therapist may offer augmentative and alternative communication (AAC) that consists of different methods (White et al., 2021), such as picture exchange communication system (PECS), flash cards, communication boards, speech generating devices (SGDs), and tablets. It has been shown that when combined with ongoing speech therapy, sign language (SL) can foster language development in children with ASD (Bonvillian, Nelson, & Rhyne, 1981). However, through this approach, completely nonverbal children with ASD are not likely to gain spoken words, as it is estimated that about 25-30% of children with ASD will never develop any form of verbal communication or will remain minimally verbal (Rose, Trembath, Keen, & Paynter, 2016).

SL relies on using hand gestures, body movements, and facial expressions to express words and phrases, and it is not the same everywhere. SL can give deaf children with ASD a way to communicate and express themselves (Shield & Meier, 2014); therefore, it could also end up being a primary way of a child with ASD to communicate. SL may connect children with ASD to a broader community of individuals who use SL for communication. Notably, American Sign Language (ASL) is the primary language of many deaf and hard-of-hearing people in North America. ASL is also used by some hearing people (American Sign Language 2022).

Although verbal communication can be extremely difficult for a child with ASD to understand and use, SL is typically easier to understand and use (Brown, 1978). Because children with ASD understand visual information more easily than verbal information (Gladfelter, Barron, & Johnson, 2019). As a lack of communication skills is frustrating for children with ASD, it leads to difficult behaviours (De Giacomo et al., 2016; McNeil, Quetsch, & Anderson, 2019). On the other hand, being a functional way of communication, SL leads to a decrease in difficult behaviours (Lal & Sanghvi, 2015).

Image processing methods and classification algorithms are essential in vision-based solutions proposed to identify SL gestures. The vision-based solutions are easier to implement and cheaper; therefore, in this paper, the performances of various classification algorithms used to classify the phonemes of ASL are compared. The remaining sections of this paper are organized as follows. The next section provides a literature review in the related domain. The third section presents information on dataset used and analysis methodology used in this study. The fourth section reports results and provides discussion on the topic. Finally, this paper is concluded in the fifth section.

2. LITERATURE REVIEW

There are common misconceptions about SL. For instance, although some parents and professionals worry that teaching SL to children with ASD can hinder their verbal communication progress and the children's ability to speak; it is false (Thompson et al., 2007). However, SL helps enhance various speech and language skills essential for fundamental learning (Toth, 2009). It has been shown that learning and using SL helps children with ASD develop verbal language (Carr, 1979). Another common misconception is that SL is only for children with a hearing impairment. But SL is also for children with limited expressive and language skills. SL can also act as a bridge for bilingual children, aiding them in learning a new language (Tomaszewski, 2001). As SL allows children with ASD to interact and play with other children, it helps children with ASD build new social skills as well as imitation skills (Bonvillian, Nelson, & Rhyne, 1981). SL can also open the lines of communication between a child with ASD and his/her parents or teacher (Bonvillian & Nelson, 1976; Simpson & Lynch, 2007). Generally, learning SL does not take too much time and it is recommended to begin with a few signs and incorporate practicing it into daily activities (Schneden, 2006).

SL can help children with ASD be able to express themselves (Schaeffer, Kollinzas, Musil, & McDowell, 1977; Carr, 1979), but also offer a number of other benefits for them. Learning and using SL will more likely lead to more spontaneous communication for children with ASD (Schaeffer, Kollinzas, Musil, & McDowell, 1977), and better social skills. Since SL is an alternative form of communication, it will possibly reduce aggression and meltdowns due to frustration at not being able to communicate (Jantzen, 2011). It may also lead to less depression and anxiety because when children with ASD make themselves be understood by others, they will more likely be happier (Tarver et al., 2021). However, while some children with ASD may find signing enjoyable, others may not. Therefore, other than SL, alternative and augmentative communication options may be offered to such children with ASD (Iacono, Trembath, & Erickson, 2016). Parents of children with ASD should learn signing if their children use it. They can learn SL through online courses, local classes, or private tutors.

Although SL offers many benefits, it is not suitable for everyone, as each child has unique strengths and weaknesses. First of all, it is important to use hands, facial features, head, and upper body carefully in SLs; however, some children with ASD have significant difficulties in motor skills (McCleery, Elliott, Sampanis, & Stefanidou, 2013). SL can involve facial expressions are used to express both linguistic information and emotions in order to have more nuanced conversation, but this is hard for children with ASD due to their having a difficulty in interpreting faces (Denmark, Atkinson, Campbell, & Swettenham, 2019; Sato et al., 2017). Most children with ASD prefer short eye contact and do not enjoy prolonged ones (Trevisan, Roberts, Lin, & Birmingham, 2017); however, eye contact is an essential part of SL when interacting with SL users who are deaf. Although self-stimulatory behaviour is not a bad thing, if a child with ASD uses his/her hands for self-stimulatory behaviours, this can confuse or distract the conversation partner (Kapp et al., 2019). Finally, although some children with ASD find SL effective and enjoyable, others do not and get more out of a different method. Therefore, using different methods for different contexts may be recommended. In contrast to common belief, SL can enhance various speech and language skills essential for fundamental learning skills (Bowman-Smart et al., 2019). With regard to speech and language development, SL can provide a number of benefits. It can allow transitioning from gestures to speaking smoothly, improve vocabulary and confidence, enhance using adjectives and adverbs, empower earlier reading and recognition of sight words, and increase expressive and receptive language skills (Baker-Ramos, 2017). SL can bridge the gap between non-verbal communication and speaking, and if it is introduced and taught early in life, it helps to enhance speech and language development (Fitzpatrick, Stevens, Garritty, & Moher, 2013). If a child learns and uses SL, his/her parents must learn, too. As well as private tutors and local classes, online courses can help for this. Each SL has its own fingerspelling forms, and vocabulary that is important and more commonly used by the child should be prioritised to learn and memorise (Lal & Sanghvi, 2015). In case of difficulty in learning the SL, the parents can be offered technological solutions. Such solutions identify SL symbols and gestures, interpret the overall meaning of the sentence and then generate visual response to the counterparty. Both vision-based approaches and data glove approaches can be used to recognise hand gestures (Trigueiros, Ribeiro, & Reis, 2014). Compared to the data glove approaches, the vision-based ones offer a simpler and probably more intuitive method of communication between a human and a computer. They also enable to recognise SL in real-time (Trigueiros, Ribeiro, & Reis, 2014).

3. METHODOLOGY

In this study, the Sign Language MNIST (https://www.kaggle.com/datasets/datamunge/sign-language-mnist) open dataset was used. The fingerspellings of ASL represent a multi-class problem involving 24 classes of letters, with J and Z excluded as they require motion (Figure 1). The training dataset contains a set of 28x28 grayscale images in PNG format of the entire alphabet, except J and Z, and is composed of a total of 27455 instances. The data in its raw form is provided as a pixel to pixel intensity [0-255] class-wise distributed XLS files.

Figure 1: Alphabet (phonemes) of ASL

In this study, as shown in Figure 2, K-Nearest Neighbours (KNN), Extra Trees, Linear Discriminant Analysis (LDA) and Rep Tree algorithms were used for the classifications and their performances were compared. To avoid overfitting, the 10-fold cross-validation method was used as the performance analysis method.

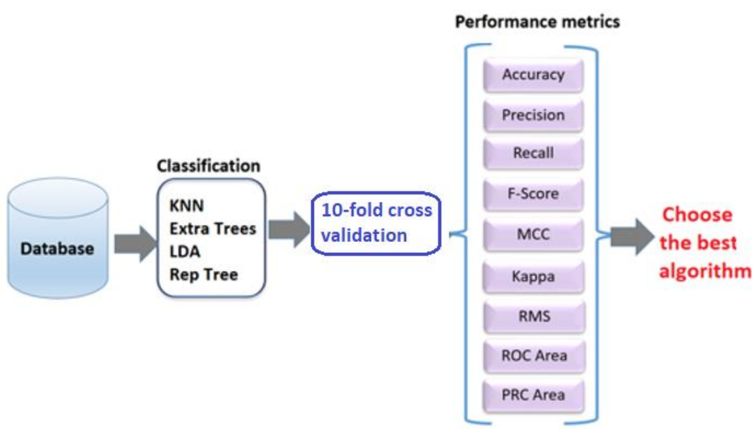

Figure 2: Methodology used in this study

3.1. Classification Algorithms

The KNN is a simple and yet effective algorithm; therefore, it is popular in studies focusing on classification and regression problems. It classifies a sample according to its proximity, i.e. distance, to other samples in the dataset (Abu Alfeilat et al., 2019). Although Euclidean distance is the commonly used distance measure of the KNN, there are others. Examples of the other distance measures that can be used by the KNN are Manhattan distance, Mahalanobis distance, Chebychev distance, Minkowski distance, and Hamming distance (Abu Alfeilat et al., 2019).

The Extra Trees is one of the decision tree algorithms that creates many unpruned decision trees from a given training dataset and is often used in classification problems (Kasliwal, 2018). As it relies on ensemble learning, it combines the predictions from many decision trees (Geurts, Ernst, & Wehenkel, 2006). The LDA was developed by R. A. Fischer in 1936 (Boedeker & Kearns, 2019). It searches for a linear combination of variables that can best separate existing classes. It can achieve good results in complex problems (Boedeker & Kearns, 2019). The Rep Tree relies on regression tree logic and first creates multiple trees at different iterations. It then selects the best of all trees produced and considers it as a representative (Weinberg & Last, 2019). Rep Tree relies on calculating the information gain with entropy and reducing the error due to variance (Weinberg & Last, 2019).

3.2. Performance Metrics

Various evaluation metrics have been proposed so that models created with classification algorithms can be evaluated, thereby determining which model produces more accurate results. True positive (TP), true negative (TN), false positive (FP) and false negative (FN) values are used in the calculation of these metrics.). It is recommended to use precision and recall metrics together, but other metrics are needed for performance evaluation, too. Because the comparison of the results of two models with low recall and high precision and vice versa is not easy and reliable. In this case, F-Score calculated by taking the harmonic average of these two metrics is used. Matthews correlation coefficient (MCC) value is very useful in case of an imbalance between the classes in the dataset (Chicco & Jurman, 2020). For a good classification, performance metrics should take values close to 1. These metrics are explained in Figure 3.

Metric and Formula	
$\text{Accuracy} = \dfrac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$	(1)
$\text{Precision} = \dfrac{\text{TP}}{\text{TP} + \text{FP}}$	(2)
$\text{Recall} = \dfrac{\text{TP}}{\text{TP} + \text{FN}}$	(3)
$\text{F} - \text{Score} = \dfrac{2}{\dfrac{1}{\text{Recall}} + \dfrac{1}{\text{Precision}}}$	(4)
$\text{MCC} = \dfrac{\text{TP} * \text{TN} - \text{FP} * \text{FN}}{\sqrt{(\text{TP} + \text{FP}) * (\text{TP} + \text{FN}) * (\text{TN} + \text{FP}) * (\text{TN} + \text{FN})}}$	(5)

Figure 3: Performance metrics and their formulas

Another metric is Cohen's Kappa statistic. The kappa statistic is basically a measure of agreement between actual and predicted classes (Delgado & Tibau, 2019). Kappa statistics are calculated with Equation (6), where $\bar{P}$(x) is the observed concordance rate and $\bar{P}$(y) is the random concordance rate.

$$Kappa = \frac{P(x)-P(y)}{1-P(y)} \tag{6}$$

the predicted, and y represents the actual, RMSE can be calculated as shown in Equation 7.

$$RMSE = \sqrt{\frac{(x_1-y_1\ )^2+\cdots.+(x_n-y_{1n}\ )^2}{n}} \tag{7}$$

ROC area and PRC area values express the areas under the drawn curves (Fawcett, 2006). For example, the ROC area value is the area under the ROC curve. In the ROC curve, while the horizontal axis shows FP rate, the vertical axis shows TP rate. ROC graphs are useful for organising classifiers and visualising their performance (Delgado & Tibau, 2019). Similar to the ROC area, the PRC area shows the area under the PRC curve. It refers to the area under the curve drawn in the PRC curve with the horizontal axis, i.e. recall, and the vertical axis, i.e. precision.

4. RESULTS

In this study, 10 different performance metrics explained in Section 2 were used to compare the success of KNN, Extra Trees, LDA and Rep Tree algorithms in the classification of ASL phonemes. The values of performance metrics obtained from 10-fold cross-validation are given in Figure 4. Considering all the performance metrics in Figure 3, the KNN algorithm demonstrated the best overall classification performance, achieving the lowest error rate. On the other hand, the Rep Tree algorithm had the worst overall performance. The parameters of the algorithms used are given in Table 1.

A confusion matrix contains basic but useful information about the results of a classification study. The parts coloured in green in the confusion matrix are TP and TN values. The TP and TN values represent the total number of the words that the algorithms predicted correctly. Other numbers in the confusion matrix indicate the number of incorrectly predicted words. The confusion matrices obtained by the algorithms from 10-fold cross-validation are given in Figure 5. The confusion matrices in Figure 4 indicate that the KNN and LDA algorithms delivered the best results. The KNN algorithm predicted almost all the letters correctly, only 1 i, 6 v letters and 1 w incorrectly. This indicates that the algorithm has difficulty in finding the letter v. The LDA algorithm, on the other hand, was found to have difficulty in detecting these letters due to incorrect predictions in the letters f, g, k, l, u, v, w, and y. When all the performance metrics are considered, it can be seen that the most successful algorithm is the KNN algorithm.

Table 1: Parameters of the algorithms used

Algorithm	Paremeters
KNN	Number of KNN neighbors 1, batchsize 100, distance function Euclidean Distance.
Extra tree	Batch size: 100, Number of attributes to randomly choose at a node (k) :1, Seed:1
LDA	The tolerance of the termination criterion (eps) : 0.001, epsilon parameter 0.1, The cost parameter (cost): C:1.
Rep Tree	Batch size: 100, Seed:1, max deep:1, Determines the amount of data used for pruning. One fold is used for pruning, the rest for growing the rules(numfold) :3, The minimum total weight of the instances in a leaf (minNum):2. The number of decimal places to be used for the output of numbers in the model (numDecimalPlaces): 2.

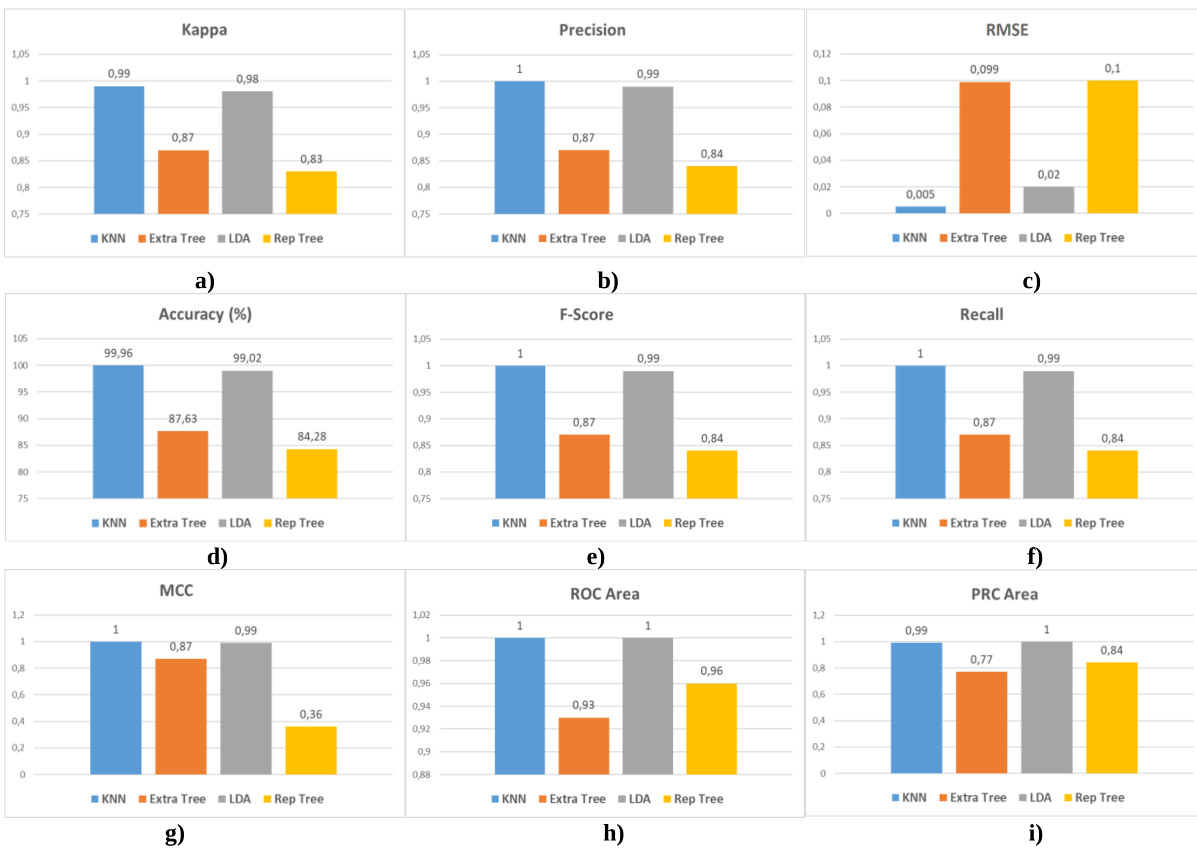

Figure 4: Performance metrics a) Kappa, b) Precision, c) RMSE, d) Accuracy, e) F-Score, f) Recall, g) MCC, h) ROC Area, i) PRC Area

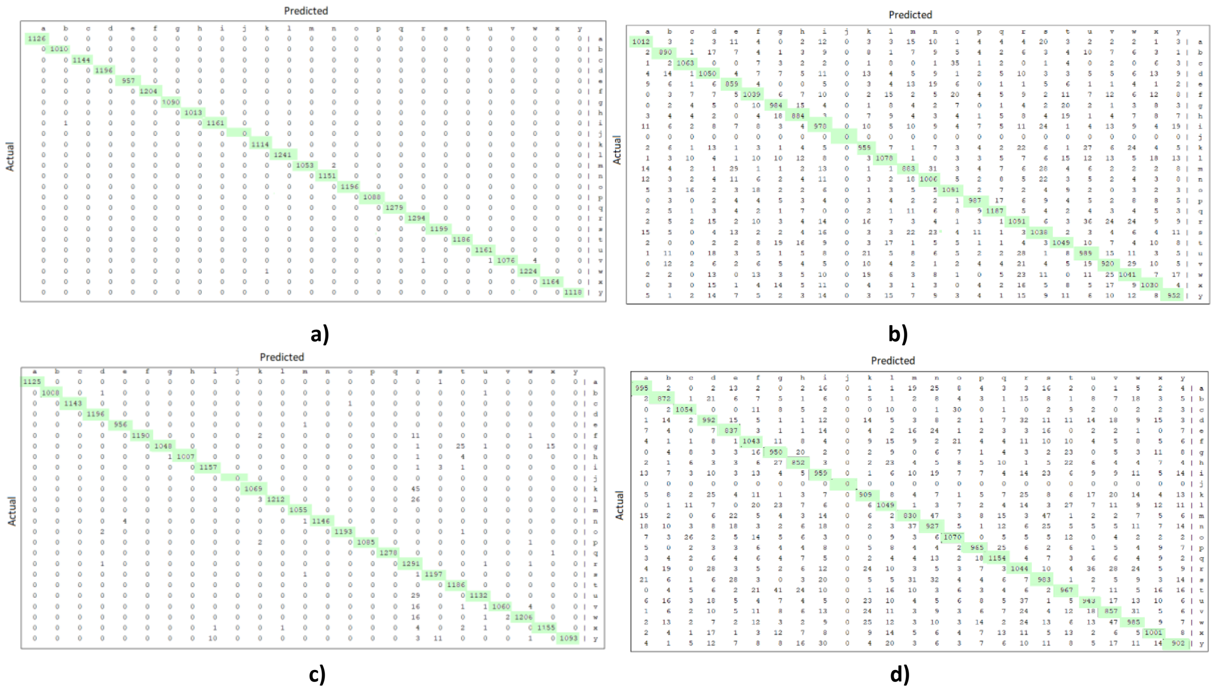

Figure 5: Confusion matrices a) The KNN, b) The Extra Trees, c) The LDA, d) The Rep Tree

When the algorithms' Time taken to build model and running times are examined, Time taken to build model KNN 0.08s, Extra tree 1.18s, LDA 0.9s, Rep tree 52.77s respectively. The running times are KNN 17 min, Extra tree 25s, LDA 9min, Rep tree 15min respectively. The fastest algorithm was Extra Trees, while KNN was the slowest.

5. DISCUSSION

Using the open dataset mentioned in the previous section, Rathi (2018) implemented a convolutional neural network (CNN) to recognise the alphabet of ASL. In deep learning, the CNN is a class of Artificial Neural Network (ANN), and it is commonly used to analyse visual imagery (Valueva et al., 2020). Although training the CNN takes a long time even across multiple graphical processing units, Rathi (2018) used two pre-trained models, Inception_v3 model (Szegedy, Vanhoucke, Ioffe, & Shlens, 2016) and MobileNet_v1 model (Howard et al., 2017). Both are open-source models and utilise the CNN at their cores. Rathi (2018) achieved an accuracy rate of 95.06% with MobileNet_v1 model and an accuracy rate of 93.36% with Inception_v3 model. In addition to the original mobile application solution proposed by Rathi (2018), the proposed solution could also be implemented in Raspberry Pi with OpenCV, and text- to-speech function can be used to achieve an improved and automated translation application.

SGDs can be used to teach language and literacy skills to children with ASD (Thunberg, Ahlsén, & Sandberg, 2007). Contrary to common belief that AAC and SGDs can obstruct the development of verbal speech, AAC helps children with ASD develop language and verbal speech faster. Because by providing a visual and auditory representation of vocabulary words, it makes combining words easier (National Academies of Sciences, Engineering, and Medicine, 2017). SGDs provided in the form of an application in a smart phone or tablet are relatively low-cost and highly portable. Examples of this are LAMP, Proloqu2go, Touch Chat, and Avaz (Proctor & Wang, 2016). Although AAC and SGDs can be quite useful to children with ASD, solutions that can help teachers who do not know SL are important because they may need to work with children with hearing impairment or children with speaking impairment. Biçek and Almalı (2020) proposed and developed a mobile application that allows educators who do not know SL to teach individuals with hearing impairment by using speech-to-text process.

Considering the numerous opportunities of virtual reality environment, Schioppo, Meyer, Fabiano, and Canavan (2020) proposed a virtual reality-based real-time system to recognise SL. The system relies on an egocentric view with a virtual reality headset along with a motion controller that consists of an optical hand tracking module to capture hand movements. In the demo, based on hand-crafted features that were extracted from the motion controller, the authors used random forest classifier to identify the 26 letters of ASL. After carrying out 10-fold cross-validation on 30 instances of each of the 26 letters, the authors achieved an accuracy of 98.33%.

6.CONCLUSION

The first step of starting to use signs is to learn the finger alphabet. Each SL comes with its own alphabet and parents are recommended to prioritise signs that their children use most often and learn vocabulary important to their families. There are commercially or freely available technological solutions that the parents can use to understand SL if they have difficulty with it. Image processing methods and classification algorithms lie on the core of these solutions; therefore, in this study, the performance of a group of classification algorithms for classifying ASL phonemes was compared. As the results show, when combined with image processing methods, classification algorithms can be used to identify ASL phonemes. In this study, the KNN achieved the best performance in terms of the used performance metrics. The proposed approach can be implemented in a smart phone or tablet or using a virtual reality headset.

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest among the authors.

CONTRIBUTIONS OF AUTHORS

E.E.: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, writing—original draft preparation.

A.T.: Methodology, investigation, resources, writing—review and editing.

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