Automatic Hand Sign Recognition: Identify Unusuality through Latent Cognizance

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Abstract. Sign language is a main communication channel among hearing disability community. Automatic sign language transcription could facilitate better communication and understanding between hearing disability community and hearing majority.

As a recent work in automatic sign language transcription has discussed, effectively handling or identifying a non-sign posture is one of the key issues. A non-sign posture is a posture unintended for sign reading and does not belong to any valid sign. A non-sign posture may arise during sign transition or simply from an unaware posture. Confidence ratio has been proposed to mitigate the issue. Confidence ratio is simple to compute and readily available without extra training. However, confidence ratio is reported to only partially address the problem. In addition, confidence ratio formulation is susceptible to computational instability.

This article proposes alternative formulations to confidence ratio, investigates an issue of non-sign identification for Thai Finger Spelling recognition, explores potential solutions and has found a promising direction. Not only does this finding address the issue of non-sign identification, it also provide some insight behind a well-learned inference machine, revealing hidden meaning and new interpretation of the underlying mechanism. Our proposed methods are evaluated and shown to be effective for non-sign detection.

Keywords: Hand sign recognition \cdot Thai Finger Spelling \cdot Open-set detection \cdot Novelty detection \cdot Zero-shot learning \cdot Inference interpretation

1 Introduction

Sign language is a main face-to-face communication channel in a hearing disability community. Like spoken languages, there are many sign languages, e.g., American Sign Language (ASL), British Sign Language (BSL), French Sign Language (LSF), Spanish Sign Language (LSE), Italian Sign Language (LIS), German Sign Language (DGS), Chinese Sign Language (CSL), Japanese Sign Language (JSL), Indo-Pakistani Sign Language (IPSL), Thai Sign Language (TSL), etc. A sign language usually has two schemes: semantic sign scheme and finger spelling scheme. A semantic sign scheme uses hand gestures, facial expressions, body parts, and actions to communicate meaning, tone, and sentiment. A finger spelling scheme uses hand postures to represent alphabets in its corresponding

language. Automatic sign language transcription would allow better communication between a deaf community and hearing majority. Sign language recognition has been subjects of various studies: visual-based approach[2, 8, 9, 11, 17] and sensory-glove-based approach[6, 10]. A recent study[9], investigating hand sign recognition for Thai Finger Spelling (TFS), has discussed issues and challenges in automatic transcription of TFS. Although the discussion is based on TFS, some issues are general across languages or even general across domains beyond sign language recognition. One of the key issues discussed in the study[9] is an issue of a non-sign or an invalid TFS sign, which may appear unintentionally during sign transition or from unaware hand postures.

The appearance of non-signs may undermine the overall transcription performance. Nakjai and Katanyukul[9] proposed a light-weight computation approach to address the issue. Sign recognition is generally based on multi-class classification, whose output is represented in softmax coding. That is, a softmax output capable of predicting one of K classes is noted $\boldsymbol{y} = [y_1 y_2 \dots y_K]^T$, whose coding bit $y_i \in [0, 1], i = 1, \dots, K$ and $\sum_{i=1}^K y_i = 1$. A softmax output \boldsymbol{y} represents predicted class k when y_k is the largest component: $k = \arg \max_i y_i$. Their approach is based on the assumption that the ratio between the largest value of the coding bit and the rest shows the confidence of the model in its class prediction. Softmax coding values have been normalized so that it can be associated to both probability interpretation and cross-entropy calculation. Despite the benefits of normalization, they use the penultimate values instead of the softmax values for rationale that some information might have been lost during the softmax activation. Penultimate values are inference values before going through softmax activation (i.e., a_k in Eq. 1). Specifically, to indicate a non-sign posture, they proposed a confidence ratio, $cr = \frac{a}{b}$, where a and b are the largest and second largest penultimate values, respectively: $a = a_m$ and $b = a_n$ where $m = \arg \max_i a_i$ and $n = \arg \max_{i \neq m} a_i$. Their confidence ratio has been reported to be effective in identifying a posture that is likely to get a wrong prediction. However, on their evaluating environment, they reported that the confidence ratio could hardly distinguish the cause of the wrong prediction whether it is a misclassified valid sign or it is a forced prediction on an invalid sign. In addition, generally each penultimate output is a real number, $a_i \in \mathbb{R}$. This nature poses a risk on confidence ratio formulation for when there is zero or a negative number, cr can be misleading or its computation can even collapse (when denominator is zero).

Our study investigates development of an automatic hand sign recognition for Thai Finger Spelling (TFS), alternative formulations to confidence ratio, a non-sign issue and potential mitigations for a non-sign issue. TFS, designated by the National Association of the Deaf in Thailand, has 25 hand postures to represent 42 Thai alphabets using single-posture and multi-posture schemas[9]. Single-posture schema directly associates a hand posture to a corresponding alphabet. Multi-posture schema associates a series of 2 to 3 hand postures to a corresponding alphabet. Based on probability interpretation of an inference output, Bayes theorem, and examining an internal structure of a commonly adopted inference model, various formulation alternatives to confidence ratio and a mitigation to a non-sign issue are investigated (Section 3). Sections 2, 4, and 5 provide related background, methodologies and experimental results, and discussion and conclusions, respectively.

2 Background

TFS hand sign recognition. A recent visual-based state-of-the-art in TFS sign recognition[9] frames hand sign recognition as a pipeline of hand localization and sign classification problem. They proposed an approach based on color scheme and contour area using Green's theorem for hand localization. Then, an image region dominated by a hand is scaled to a pre-defined size (i.e., 64×64) and passed through a classifier, implemented with a convolution neural network. The classifier predicts the most likely class out of the 25 pre-defined classes, each corresponding to a valid TFS sign.

Most visual-based TFS sign recognition studies[9, 11, 17] focus on a static image. However, a practical system should anticipate video and streaming data, where unintended postures may be passed through the pipeline and cause confusion to the final transcription result. Unintended postures can accidentally match valid signs. This challenging case is worth further investigation and could be addressed through a language model. However, even when the unintended postures do not match any of the valid signs, a classifier is forced to predict one out of its pre-defined classes. No matter which class it predicts, the prediction is wrong. This could cause immediate confusion on its recognition result or this can undermine performance of its subsequence process in case of using this recognition as a part of a larger system.

Novelty, anomaly, outlier detections, and zero-shot learning. A conventional classifier specifies a fixed number of classes it can predict and forced to predict. This constraint allows it to be efficiently optimized to its classification task, but it has a drawback, which is more apparent when the assumption of all-inclusive classes is strongly violated. The concept of flagging out an instance belonging to a class that an inference machine has not seen at all in the training phase is a common issue and a general concern beyond sign language recognition. The issue has been extensively studied under various terms¹, e.g., novelty detection, anomaly detection, outlier detection, and zero-shot learning.

Pimentel et al.[13] summarize a general direction in novelty detection. That is, a detection method usually builds a model using training data containing no examples or very few examples of the novel classes. Then, somehow depending on approaches, a novelty score s is assigned to the data under question \boldsymbol{x} and the final novelty judgement is decided by thresholding, i.e., the data \boldsymbol{x} is judged a novelty (belonging to a new class) when $s(\boldsymbol{x}) > \tau$ for τ is a pre-defined threshold.

To obtain the novelty score, various approaches have been examined. Pimentel et al.[13] categorize novelty detection into 5 approaches: probabilistic,

¹ Definition of novelty, anomaly, outlier, and zero-shot may be slightly different. Approaches may be various[13, 19], but they are generally addressing a similar concern.

distance-based, reconstruction-based, domain-based, and information-theoretic based techniques. Probabilistic approach relies on estimating probability density function (pdf) of the data. A sample \boldsymbol{x} is tested by thresholding the value of its pdf: $pdf(\boldsymbol{x}) < \tau$ indicates \boldsymbol{x} being novelty. Training data is used to estimate the pdf. Although this approach has a strong theoretical support, estimating pdf in practice requires a powerful generative model along with an efficient mechanism to train it. Generative model at its fullest potential could provide greater inference capacities on data, such as expressive representation, reconstruction, speculation, generation, and structured prediction. Its applicability is much beyond novelty detection. However, high-dimension structured data renders this requirement very challenging. A computationally traceable generative model is a subject of highly active research on its own right. Another related issue is to determine a sensible value for τ , in which many studies[1,3,15] have resorted to extreme value theory (EVT)[12].

Distance-based approach is presumably [13] based on an assumption that data seen in a training process is tightly clustered and data of new types locate far from their nearest neighbors in the data space. Either a concept of nearest neighbors[20] or of clustering[7] is used. Roughly speaking, a novelty score is defined either by a distance between a sample x and its nearest neighbors or by a distance between x and its closest cluster centroids. Distance is often measured with Euclidean or Mahalanobis distance. The approach relies on mechanism to identify the nearest neighbors or the nearest clusters. This usually is computationally intensive and becomes a key factor attributed to its scalability issue in terms of data size and data dimensions. Reconstruction-based approach involves building a re-constructive model, sometimes called "auto-encoder," which learns to find a compact representation of input and reproduce it as an output. Then, to test a sample, the sample is put through a reconstruction process and a degree of dissimilarity between the sample and its reconstructed counterpart is used as a novelty score. Hawkins et al.[4] uses a 3-hidden-layer ANN learned to reproduce its input. Therefore, numbers of input and output nodes are equal. The ANN is structured to have numbers of nodes in the hidden layers smaller than a number of input or output nodes in order to force ANN to learn compressed representation of the data. Any sample that cannot be reconstructed well is taken for novelty, as this infers that its internal characteristics do not align with the compressed structure fine tuned to the training data. This approach may also resort to distance measurement for a degree of dissimilarity, but it does not require to search for the nearest neighbors. Therefore, once a good auto-encoder is obtained, scalability is not as an issue as in a distancebased approach. Domain-based approach is related to building a boundary of the data domain in feature space. Any sample is considered novelty if its location on feature space lies outside the boundary. Schölkopf et al. [16] proposed one-class SVM for novelty detection. Its key factors are to have SVM learn to build a boundary in feature space to adequately cover most training examples. while having a user-defined parameter to control a degree to allow some training samples to be outside the boundary. This compromising mechanism is a countermeasure to outliers in training data. The last approach is information-theoretic. It involves measurement of information content in the data. It assumes that samples of novelty increase information content in the dataset significantly. As their task is to remove outliers from data, He et al.[5] uses a decrease in entropy of a dataset after removal of the samples to indicate a degree that the samples are outliers. The samples are heuristically searched. Pimentel et al.[13] noted that this approach often requires an information measure that is sensitive enough to pick up the effect of novelty samples, especially when a number of these samples are small.

Based on this categorization[13], probabilistic approach is closest to the direction our work is taking. However, unlike many early works, firstly, rather than requiring a dedicated model, our proposed method builds upon a well-adopted classifier. It can be used with an already-trained model without requirement for re-training. Secondly, most works including a notable work of OpenMax[1] determine a degree of novelty of a sample by how unlikely it is to belong to any seen classes. Another word, most previous works deduce probability of the sample being novelty by examining every probability of the sample being of the seen class, i.e., small values of $Pr[class = i|\mathbf{x}]$, for all $i = 1, \ldots, K$ are used to deduce the degree of novelty of \mathbf{x} . Our work follows our interpretation of softmax output, i.e., $y_k \equiv Pr[class = k|s, \mathbf{x}]$, where s represents a state of a valid sign (not novelty). How likely sample \mathbf{x} is a novelty then can be directly deduced.

3 Prediction confidence and non-sign identification

Confidence score. Since y_k is associated with a probability of being in class k and y_k is generally obtained through a softmax mechanism (Eq. 1), our study develops alternative formulations, as shown in Table 1. Since y_k has a direct probability interpretation, formulation cs_1 is straightforward. Formulation cs_2 is associated to a logarithm of probability. Formulation cs_3 is similar to confidence ratio, but it is an attempt to link an empirical utility to a theoretical rationale (probabilistic interpretation). In addition, formulation cs_3 is preferably in term of computational cost and stability. Formulation cs_4 , a logit function, has a more direct interpretation of the starting assumption that the confidence is high when probability of the predicted class is much higher than the rest.

Latent cognizance. Given the input image \boldsymbol{x} , the predicted sign in softmax coding $\boldsymbol{y} \in \mathbb{R}^{K}$ is derived through a softmax activation: for $k = 1, \ldots, K$,

$$y_k = \frac{e^{a_k}}{\sum_{i=1}^K e^{a_i}},$$
(1)

where a_k is the k^{th} component of penultimate output, which has K defined classes. Each y_k can be interpreted as a probability that the given image belongs to sign class k, or more precisely a probability that the given valid input belongs to class k. That is,

$$y_k \equiv \Pr[k|s, \boldsymbol{x}] \tag{2}$$

Table 1. Formulations under investigation for confidence score and lalent cognizance function. Softmax value $y_l = \frac{e^{a_l}}{\sum_{i=1}^{K} e^{a_i}}$, where K is a number of predefined classes; a_l is a penultimate value; k and j are indices of the largest and the second largest components, respectively.

Confider	nce $cs_1 = y_k$	$cs_2 = a_k$	$cs_3 = \log\left(\frac{y_k}{y_j}\right)$	$cs_4 = \log\left(\frac{y_k}{1 - y_k}\right)$
score			$=a_k-a_j$	
Latent				
cognizance \tilde{g}_0	$(a) = a \tilde{g}_1(a) = e^a$	$ \tilde{g}_2(a) = a^2$	$\tilde{g}_3(a) = a^3$	$\tilde{g}_4(a) = a $

where k indicates one of the K valid classes, \boldsymbol{x} is the input under question, and s indicates that \boldsymbol{x} is representing one of the valid classes (being a sign). For conciseness, conditioning on \boldsymbol{x} may be omitted, e.g., Eq. 2 may be written as $y_k = Pr[k|s]$. Noted that, this insight is distinct to a common interpretation[1] that softmax coding bit y_k of a well-learned inference model estimates probability of being in class k, i.e., $y_k = Pr[k|\boldsymbol{x}]$. This common notion does not emphasize its conditioning on an inclusiveness of all pre-defined classes.

To identify a non-sign is another side of determining the probability of being a sign: $Pr[\bar{s}|\boldsymbol{x}] = 1 - Pr[s|\boldsymbol{x}]$. To deduce $Pr[s|\boldsymbol{x}]$, or concisely Pr[s], consider Bayesian relation: $Pr[k|s] = \frac{Pr[k,s]}{\sum_{i=1}^{K} Pr[i,s]}$ where Pr[k,s] is a joint probability. Given the Bayesian relation, inference mechanism (Eq. 1), and our interpretation of y_k (Eq. 2), the following relation is found:

$$\frac{e^{a_k}}{\sum_{i=1}^{K} e^{a_i}} = \frac{Pr[k,s]}{\sum_{i=1}^{K} Pr[i,s]}.$$
(3)

It is noticeable that term e^{a_k} is in the same structure as joint probability Pr[k, s] is. Here, we draw the assumption that penultimate value a_k relates to joint probability Pr[k, s] through an unknown function $u : a_k(\boldsymbol{x}) \mapsto Pr[k, s|\boldsymbol{x}]$. Theoretically, this unknown function is difficult to exactly characterize. In practice, even without exact characteristics of this mapping, a good approximate is enough to accomplish a task of identifying a non-sign. Supposed there exists an approximate mapping g, i.e., $g(a_k) \approx Pr[k, s]$, therefore given $g(a_i)$'s, a non-sign can be identified by $Pr[s|\boldsymbol{x}] = \sum_i Pr[i, s|\boldsymbol{x}] \approx \sum_i g(a_i(\boldsymbol{x}))$. Further refining, to lessen burden on enforcing proper probability properties on g, define a "latent cognizance" function \tilde{g} such that $\tilde{g}(a_i(\boldsymbol{x})) \propto g(a_i(\boldsymbol{x}))$. Consequently, define primary and secondary latent cognizances as the following relations, respectively:

$$\tilde{g}(a_i(\boldsymbol{x})) \propto Pr[i, s|\boldsymbol{x}],$$
(4)

$$\sum_{i} \tilde{g}(a_{i}(\boldsymbol{x})) \propto Pr[s|\boldsymbol{x}].$$
(5)

Various formulations (Table 1) are investigated for an effective latent cognizance function. Identity \tilde{g}_0 is chosen for its simplicity. Exponential \tilde{g}_1 is chosen for its immediate reflection on Eq. 3. It should be noted that a study on a whole family of $\tilde{g} = m \cdot e^a$, where *m* is a constant, is worth further investigation. Other formulations are intuitively included on an exploratory purpose.

4 Experiments

Various formulations of confidence score and choices of latent cognizance are evaluated on TFS sign recognition system. Our TFS sign recognition follows the current state-of-the-art in visual TFS sign recognition [9] with a modification of convolution neural network (CNN) configuration and its input resolution. Instead of a 64×64 gray-scale image, our work uses a 128×128 color image as an input for CNN. Our CNN configuration uses a VGG-16[18] with the 2 fully-connected layers each having 2048 nodes, instead of 3 fully-connected layers in the original VGG-16. Fig. 1 illustrates a processing pipeline of our TFS sign recognition.



Fig. 1. Processing pipeline of our TFS sign recognition.

Sign data. The main dataset contains images of 25 valid TFS sign postures. Each valid TFS sign data is collected from 12 signers and posed 5 times by each signer. That results in a total number of 1500 images (5 times $\times 25$ postures $\times 12$ signers), which are augmented to 15000 images. All augmented images are visually inspected for human readability and semantic integrity. Every image is a color image with a resolution of approximately 800×600 pixels.

Experimentation. The data is separated by signer into training set (11250 images from 9 signers making up as 75%) and test set (the 3750 images from the 3 signers, making up 25%). The experiments are conducted for 10 repetitions in a 10-fold manner. Specifically, each repetition separates data differently, e.g., the 1^{st} fold uses data from signers 1, 2, and 3 for test and uses the rest for training; the 2^{nd} fold uses data from signers 2, 3, and 4 for test; and so on till the last fold using data from signers 10, 1, and 2 for test.

The mean Average Precision (mAP), commonly used in object detection[14], is a key performance measurement for evaluation of our TFS sign recognition. Area under curve (AUC) and receiver operating characteristic (ROC) are used

to evaluate effectiveness of various formulations for confidence score and latent cognizance. AUC is often referred to an estimate area under Precision-Recall curve, while ROC is usually referred to an estimate area under Detection-Rate–False-Alarm-Rate curve. However, generally both areas are equivalent. We use them to differentiate the purpose of our evaluation rather than taking them as different performance metrics. AUC is used for identification of samples not to be correctly predicted². It is more direct to measure a quality of a replacement for the confidence ratio. ROC is used for identifying non-sign samples³. It is more direct to the very issue of non-sign postures.

Non-sign data. In addition to the sign dataset, a non-sign dataset containing mixed-posing invalid TFS sign postures is used to evaluate non-sign identification methods. The invalid TFS posture data is collected from a signer and augmented to 1122 images. All has been visually inspected that they all are readable and do not accidentally match to any of the 25 valid signs.

Results. Table 2 shows TFS recognition performance of the previous studies and our work. The high performing mAP (97.59%) indicates that the model is welllearned. All data are shown to be non-normal distributed, based on Lilliefors test at 0.05 level. Wilcoxon rank-sum test is conducted on each treatment for comparing (1) difference between CP and IP, (2) difference between CP and NS, and (3) difference between IP and NS. The notations CP, IP, and NS represent samples being correctly predicted, being misclassified, and being a non-sign, respectively. At 0.01 level, Wilcoxon rank-sum test confirms all 3 differences in all treatments (including confidence ratio, 4 formulations for confidence score, and 5 latent cognizance functions). Figure 2 shows boxplots of all treatments. Although the significance tests confirm that the 3 groups can be distinguishable using any of the treatments, the boxplots show a wide range of degrees of distinguishment, e.g., cognizance $\tilde{g} = a^3$ (4th plot in Fig. 2) seems to be easier than others on thresholding the 3 cases. To measure a degree of effectiveness, Tables 3 and 4 provide AUC and ROC for various methods under investigation. Noted that, since treatment \tilde{q}_0 gives results in a different manner than others: a higher value associates to a non-sign (c.f. a lower value in others), the evaluation logic is adjusted accordingly.

On finding an alternative to confidence ratio, maximal penultimate output a_k seems to be a good replacement such that it provides the largest AUC (0.934) and it is simple to obtain (no extra computation, thus no risk of computational instability). On addressing a non-sign issue, latent cognizance with cubic function $\tilde{g}(a) = a^3$ gives the best ROC (0.929). Its smoothed estimate densities⁴ of non-sign samples (NS) and sign samples (combining CP and IP) are shown on the

 $^{^2}$ Positive is defined to be a sample of either a non-sign or an incorrect prediction.

 $^{^{3}}$ Positive is defined to be a non-sign.

⁴ A normalized Gaussian-smoothing version of histogram produced through smoothed density estimates of ggplot2 (http://ggplot2.tidyverse.org) with default parameters.

left of Fig. 3. Plots of detection rate and false alarm rate of the 4 strongest candidates are shown on the right of Fig. 3.

Method				Performance
	Coverage	(# images)	factors	
Chansri and Srinonchat[2]	16 signs		Kinect 3D camera, HOG and ANN	
Pariwat and Seresangtakul[11]	15 signs	375	SVM	91.20%
Silanon[17]	21 signs	2100	HOG and ANN	78.00%
Nakjai and Katanyukul[9]	25 signs	1375	Hand Extraction and CNN	91.26%
Our work	25 signs	15000	Hand Extraction and VGG-16	97.59%

Table 2. Performance of visual-based TFS sign recognition.

Table 3. Evaluation of confidence score formulations.

	$cr = \frac{a_k}{a_j}$	$cs_1 = y_k$	$cs_2 = a_k$	$cs_3 = a_k - a_j$	$cs_4 = \log\left(\frac{y_k}{1 - y_k}\right)$
AUC	0.814	0.919	0.934	0.900	0.919
ROC	0.740	0.879	0.921	0.847	0.879

Table 4. Evaluation of various \tilde{g} formulations on $\sum_{i} \tilde{g}(a_i) \propto Pr[s]$.

	Identity	Exponential			Absolute
	$\tilde{g}_0(a) = a$	$\tilde{g}_1(a) = e^a$	$\tilde{g}_2(a) = a^2$	$\tilde{g}_3(a) = a^3$	$\tilde{g}_4(a) = a $
AUC	0.437	0.930	0.855	0.934	0.737
ROC	0.419	0.920	0.845	0.929	0.726

5 Discussion and Conclusions

The cubic function $\tilde{g}(a) = a^3$ has shown to be the best cognizance function among other candidates, including exponential $\tilde{g}(a) = e^a$. In addition, the cubic cognizance has ROC part to the max-penultimate confidence score. On the other hand, the max-penultimate confidence score also provide a competitive ROC and could be used to identify non-sign samples as well. Noted that OpenMax—a notable work in novelty detection—uses penultimate output as one of its crucial parts to identify novelties. Our finding could contribute to the development of OpenMax. A study of using cubic cognizance in OpenMax system may be

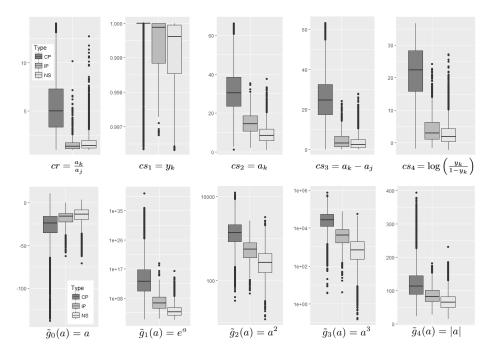


Fig. 2. Upper: Boxplots of confidence ratio and candidates for confidence score. Y-axis shows treatment values in linear scale. Lower: Boxplots of 5 candidates for latent cognizance function. Y-axis shows $\sum_i \tilde{g}(a_i)$ values (\tilde{g}_0 and \tilde{g}_4 in linear scale; the rest in log scale). Boxplots are shown in 3 groups: CP for correctly classified samples; IP for misclassified samples; NS for non-sign samples.

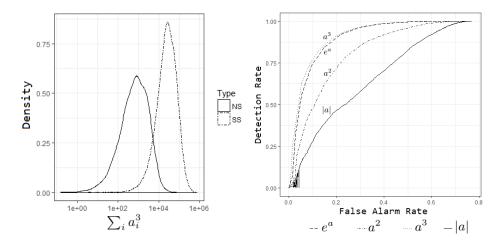


Fig. 3. (a) Illustration of smoothed estimated densities of sign (denoted SS) and nonsign (denoted NS) data over $\sum_i a_i^3$. (b) Detection rate versus false alarm rate curves of the 4 strongest candidates.

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another promising direction, since it is shown to be more effective than penultimate output. Another point worth noting is that the previous work[9] evaluated confidence score on identifying non-signs and could not confirm its effectiveness with the significance tests. Their results agree with our early experiments when using a lower resolution image, a smaller CNN structure, and training and testing on smaller datasets. In our early experiment, only a few of the treatments could be confirmed for non-sign identification. Those that were confirmed are consistent with ROC presented here. This observation implies a strong relation between state of the inference model and non-sign-identification effectiveness. This relation and its details should be systematically investigated. Regarding applications of the techniques, thresholding can be used and a proper value for threshold is needed to be determined. This can be simply achieved through tracing the Detection-Rate–False-Alarm-Rate curve with the corresponding threshold values. Alternatively, the proper threshold can be determined based on Extreme Value Theory, like many previous studies [1, 3, 15]. Another interesting research direction is to find a similar solution for other inference families. Our techniques target a softmax-based classifier, which is well-adopted especially in artificial neural network. However, Support Vector Machine (SVM), another well-adopted classifier, is built on a different paradigm. Application of either confidence score or latent cognizance to SVM might not work or might be totally irrelevant. Investigation into the issue on other inference paradigms could provide a unified insight of the underlying inference mechanism and it could be beneficial beyond addressing the novelty issue. Regarding starting assumptions, high ROC values of exponential and cubic cognizances support our new interpretation and its following assumptions. However, the penultimate output, according to our new interpretation, has relation $a_k(\mathbf{x}) = \log(Pr[k|s, \mathbf{x}]) + C$, where $C = -\log \sum_{i} a_i(\boldsymbol{x})$. This relation only partially agrees with the experimental results. High value of AUC agrees with $\log(Pr[k|s, x])$ that a class is confidently classified, but Pr[k|s, x] alone is not enough to determine a nonsign, which needs $Pr[\bar{s}|\boldsymbol{x}]$. This may imply that our research is going on a right direction, but it still needs more investigation to complete the picture.

In brief, our study investigates (1) alternatives to confidence ratio and (2) methods to identify a non-sign. The max-penultimate output is shown to be a good replacement for confidence ratio in terms of detection performance and simplicity. Its large value associates to a sample likely to be correctly classified and vice versa. The cognizance $\sum_i a_i^3$ is shown to be a good indicator for a non-sign such that $\sum_i a_i^3(\mathbf{x}) \propto \Pr[s|\mathbf{x}]$, or low value of $\sum_i a_i^3(\mathbf{x})$ associates to a non-sign sample. To warp up our article, our findings give an insight into a softmax-based inference machine and provide a tool to measure a degree of confidence in the prediction result as well as a tool to identify a novelty or an anomaly. The implications may go beyond our current scope of TFS hand-sign recognition and contribute to novelty detection, open-set recognition, and other similar concepts. Latent cognizance is very satisfactory for its simplicity and effectiveness in identifying non-signs. These would help improve an overall

quality of the translation, which in turn hopefully leads to a better understanding among people of different physical backgrounds.

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