The Effect of Maxblur-pooling in Neural Networks on Shift-invariance Issue in Various Biological Signal Classification Tasks

Xianyin Hu, Shangyin Zou, Yuki Ban and Shin'ichi Warisawa

Development of Human and Engineered Environmental Studies, The Graduate School of Frontier Sciences, The University of Tokyo, Kashiwa, Chiba, Japan

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Abstract: Modern neural networks are widely employed in bio-signal processing due to their effectiveness. However, recent research showed that neural networks for image recognition is not shift-invariant as it was assumed, while it is an important property in bio-signal processing. Fortunately, a simple methodology was proposed referred to as Maxblur-pooling to improve the shift-invariance of neural networks for image recognition. However, the corresponding issue in the domain of bio-signal processing remains untouched. To verify the shift-invariance of neural networks when applied to bio-signal processing, we performed two experiments across different tasks and types of bio-signals. One is Atrial Fibrillation (AF) detection from R-R interval and the other is emotion recognition from multi-channel EEG. We were able to show that the lack of shift-invariance also happens in temporal bio-signal classification. In the AF detection task, we succeed to validate the effectiveness of Maxblur-pooling, which demonstrating improvements in both accuracy (2%-13%) and consistency (8%-15%) compared to the baseline. While for the emotion recognition task, we did not observe any improvements using Maxblur-pooling. Our research provided empirical knowledge for developing real-time diagnose systems that is stable to temporal shifts.

1 INTRODUCTION

Deep learning approaches have achieved great success in the field of image recognition and natural language processing. In recent years, deep neural networks are also widely employed in biosignal processing served as feature extractors and pattern classifiers. For example, the most commonly investigated biosignal is electrocardiogram (ECG). Work by Acharya et al. (Acharya et al., 2017) used an 11-layer deep CNN to automatically detect arrhythmias. Another popular field of bio-signal classification using neural networks is Electroencephalogram (EEG). Tripathi et al. applied deep neural networks and convolutional neural networks to emotion recognition and gained rather high accuracy (Tripathi et al., 2017).

In most of the automatic diagnosis systems modeled as bio-signal classification task, there are usually two steps, the first step is feature extraction and the second step is pattern classification. In the first step, temporal shift-invariance, also referred to as time invariance or translation invariance (Mitra and Kaiser, 1993), is required. Temporal shift-invariance simply means that if you shift the input signal along the time axis by an arbitrary amount, as long as the ground truth does not change, all the features extracted should also stay the same. The ideal extracted features should be only related to the final target while remaining irrelevant to time. That is, the contemporaneous features extracted from a given series of the input raw signals should not depend on when the input occurs.

Someone may get confused with the statement:temporal shift-invariance is expected in biosignal processing. They may consider the change instead of the invariance should be expected since there exists so many analysis performed on moving windows to track the temporal evolution. In fact, models that do biosignal classification tasks are exactly time-invariant systems. It can be easily understand by comparing between time-variant system and time-invariant system. In a time-variant system, for the same input that happens at differnt time, the output is different. In a time-invariant system, for the same input that happens at differnt time, the output is the same. The temporal evolution to be tracked is not the evolution of the time itself, but the evolution of the parameters and behaviors in the input signals along the time. According to the definition of time-invariant system (Oppenheim, 1997), if a classifier depends only indirectly on the time-domain (via the input function, for example), then that is a sys-

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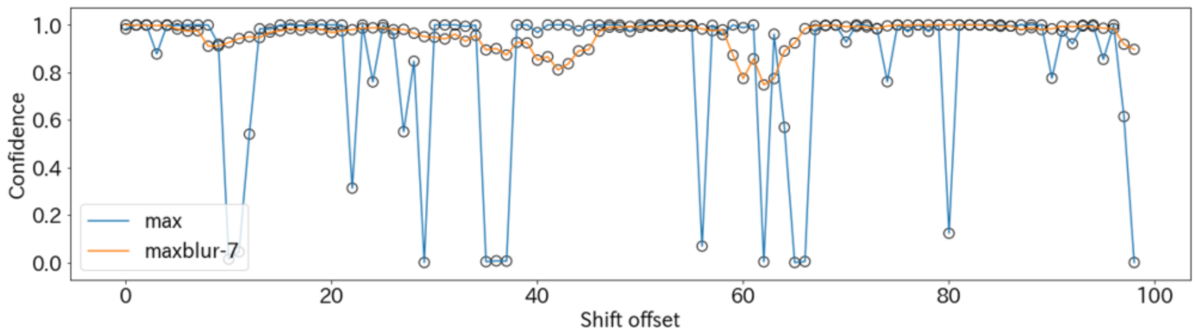


Figure 1: **The temporal shift-invariance is lacked in modern neural networks for AF detection task and Maxblur-pooling technique improved shift-invariance.** The horizontal axis is the shift offset applied to the input RRI segment and the vertical axis is the probability of making the correct estimation. We observed a drastic change of the confidence in the output of the baseline model using Max-pooling while the output of the model using Maxblur-pooling is more stable. This figure generated from the outputs of 151-th RRI segment to 251-th RRI segment in the recording of No.07162. (Referring to the expression $S(x_i, k)$ in Figure.3, here $i = 151$ and $k = 1, 2, 3, \ldots, 99$).

tem that would be considered time-invariant. In our cases, biosignal classifiers depend only indirectly on the time-domain via the biosignals (time-dependent function). Thus, the biosignal classifiers satisfied the definition and should be modeled as time-invariance systems.

Temporal shift-invariance is always addressed in the traditional analysis method in biosignal processing. For example, the discrete wavelet transform (DWT) is a commonly used time-frequency analysis and signal-coding tool to extract suitable features from raw biosignals (Addison et al., 2009), but it is also well-known for its drawbacks of lacking temporal shift-invariance. To solve the problem, a set of methods was proposed to overcome the problem to maintain temporal shift-invariance, such as the stationary wavelet transform (SWT) (Addison et al., 2009), adaptive wavelet transform (Xiong et al., 2000), etc.

Maintaining a high temporal shift-invariance is especially important and a challenging issue in developing real-time disease diagnosis systems. Real-time analysis of patient data during medical procedures can provide vital diagnostic feedback that significantly improves chances of success. The term ”real-time” means the system should response immediately to the input. In other words, the real-time system is required to output a stream with a sampling rate that is same with or near to the sampling rate of its input signal. If the system has low temporal shift-invariance, the output will suffer drastic change even when the input is shifted by a very small offset, which is not desirable.

Although the temporal shift-invariance has been addressed in traditional analysis methods of biosignals, researchers utilized modern neural network technology have neglected this important property. The reason is that these researchers take it for granted that the neural network approach is temporal shift-invariant and does not verify that.

In fact, in the first place, the basic structures that make up modern neural networks are designed under the motivation of maintaining shift-invariance. Proceeding researches believed that neural networks can acquire shift-invariance from both the architecture and the parameter.

For the way of acquiring from the architecture, layers with shared weights and layers of downsampling are proposed. For example, in convolutional neural networks (CNN), the weights of the filters in convolution layers are shared across all patches of the image - so the weights learned can be invariant to position. And max-pooling layer, by taking the max value of the pixel in the patch, approximate translation invariance can be gained since subsequent layers of the CNN don’t care about the specific position in the patch that the max value was in. Similarly, in recurrent neural networks (RNN), weights are shared across time to gain temporal shift-invariance.

For the way of acquiring from parameter, a commonly used approach is to do data augmentation by adding shifted data into the training set, then expect the weights of the neural networks to learn shift-invariance from the large amount of data.

It has been recently proved in the task of image recognition that the neural network is not shift-invariant as we expected (Azulay and Weiss, 2019). However, in the field of biosignal processing, the corresponding issue remained untouched. Therefore, it is necessary to verify whether the neural networks applied in bio-signal processing also lack temporal shift-invariance.

A novel methodology named Maxblur-pooling

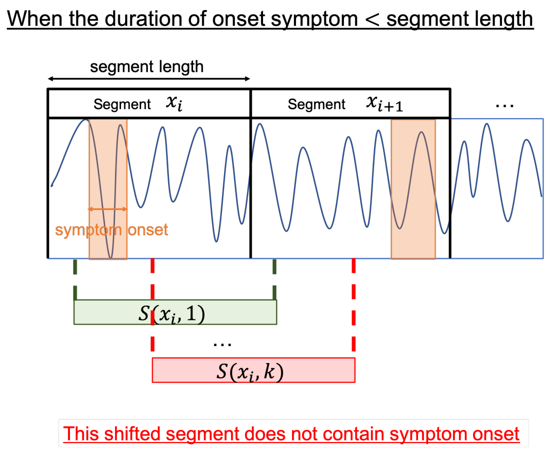


Figure 2: **Testbeds selection criteria.** A situation when the duration of onset symptom is less than segment length and we will not select the task to be our testbed. We denoted $S(x_i, s)$ as given the input segment x_i a temporal shift s. Although the shifted segment $S(x_i, 1)$ contains the symptom, the shfited segment $S(x_i, s)$ doesn't.

was proposed by Zhang to overcome the drawback of lacking shift-invariance in modern neural networks (Zhang, 2019). This method has been validated in the task of image recognition and image generation across several challenging datasets such as ImageNet. Zhang held that shift-invariance is lost because of the down-sampling in the pooling layer. However, shift-invariance can be simply fixed if features are extracted densely. This motivated them to break the Max-pooling layer in modern neural networks into two operations: (1) evaluating the max operator densely and (2) naive subsampling. They proposed to add low-pass (Gaussian) filters between them as a means of anti-aliasing. This viewpoint enables low-pass filtering to augment, rather than replace Max-pooling layers. As a result, they proved the anti-aliasing and Max-pooling can be combined in a novel way and shifts in the input leave the output relatively unaffected (shift-invariance). Although this method gained success in the task of image recognition, there is no guarantee that this method could generalize well to the neural networks that process biosignals for the following two reasons. Firstly, the Gaussian low-pass filter of Maxblur-pooling is widely used in image processing served as a smoothing filter, while in the bio-signal processing, most of the researches use Savitzky-Golay filter (Savitzky and Golay, 1964) to smooth the bio-signals. The Savitzky-Golay filter is widely used for its main advantage to preserve features of the signal such as maxima, minima, and width, which are usually flattened by the Gaussian filter. Secondly, concerning the frequency domain analysis, the low-pass filter of Maxblur-pooling has a side-effect that cut off some high-frequency components. In image processing, high-frequency components are usually conceived noise or are not necessary for the recognition and should be filtered. While in biosignals processing, although it's case by case, a large range of frequency components should be taken into account. We concerned the Maxblur-pooling employing the low-pass Gaussian filter may lose important features of signals such as maxima and high-frequency components for bio-signal processing tasks, so we can't say it certain that it will also improve when applied to bio-signals.

Thus, the effectiveness of Maxblur-pooling and its generalizability to biosignal processing is under discussion and needed validation.

In this work, we performed experiments on two datasets using different biosignal, one is atrial fibrillation (AF) detection from R-R interval and the other is effective estimation from EEG. The contributions can be summarized as follows:

- We showed the problem that neural networks lack shift-invariance also happens when tackling with biosignals. As demonstrated in Fig. 1, outputs of the baseline neural network using max-pooling suffer drastic changes according to temporal shifts.
- We showed that Maxblur-pooling improved accuracy (2%-13%), as well as consistency (8%-15%) in the task of AF detection, compared to the baseline using max-pooling.
- We did not observe improvements between the Maxblur-pooling and the baseline in the task of affective estimation, indicating that this method performed poorly to process the EEG signal. The reason was discussed that the blurring behavior of Maxblur-pooling lost too much information on the high-frequency components which is necessary for the effective estimation to estimate human emotion.
- Our work provided empirical knowledge for developing and designing neural networks for real-time diagnose systems that is stable and robust to temporal shifts.

2 TESTBEDS & EVALUATION

In this section, we described the two testbeds selected to perform the validation and the selection criteria. Then we described the metrics to evaluate the effectiveness of the Maxblur-pooling method.

2.1 Testbeds Selection Criteria

Our criteria to select proper testbeds was as follows: 1) The task is to do biological signal classification. 2) The duration of the true onset symptoms must be longer than the segment length of the input signal in the dataset.

In Fig. 2 we demonstrated an example of how a testbed does not satisfy our criteria. When the duration of symptom onsets is less than the segment length, it will happen that a shifted segment doesn't contain symptoms. So in such a task, we will never know the ground truth of each shifted segment.

The tasks in which different output labels were annotated between sessions satisfy the criteria. For example, in emotion recognition, participants were asked to watch videos that evoke various emotions. The time of watching a video served as a session. In this case, the duration of a session, also known as the duration of onset symptoms, is always longer than the segment length. For the tasks that can have different labels inside one session, investigation of the task itself is needed to determine whether it satisfies the criteria. Here we take the sleep apnea detection as an example that does not reach the criteria. In the task of sleep apnea detection (Penzel et al., 2000), the ground truth indicating the presence or absence of apnea was annotated by human experts by every one minute. Apnea is defined to happen when complete pauses in breathing appear lasting at least 10 seconds during sleep. However, the duration of onset symptom (10 seconds) is much shorter than the segment length which is one minute. So there is no guarantee that the shifted ECG segment also contains the onset symptom that makes it an apneic segment. Following the above criteria, we selected two databases that can be used for the verification of shift-invariance.

2.2 Testbeds

Atrial Fibrillation (AF) Detection. We used MIT-BIH atrial fibrillation database (Moody, 1983) for the task of atrial fibrillation (AF) detection. This database includes 25 long-term ECG recordings of human subjects with normal heart rhythm and atrial fibrillation. The R peaks were annotated manually by human experts, so we can calculate R-R intervals from the annotated files directly without pre-processing. We used 100 R-R interval segments as input. Since the duration of atrial fibrillation usually lasts for hours or even days, and the segment length is about less than two minutes for 100 R-R intervals, the test-bed satisfies the selection criteria.

Emotion Recognition. We adopted the public SEED_IV Emotion Dataset (Zheng et al., 2018) for the task of emotion recognition. The SEED_IV dataset contains 62 channels of EEG and eye movement data of four different emotions—happy, sad, fear, and neutral. In this work, we used the EEG part of the dataset. The EEG data is of 200Hz sampling rate, obtained from a total of 15 subjects during experimental sessions conducted in 3 separate days. For each emotion stimulation, the subjects were asked to watch a two-minute video. Therefore EEG data of a label is about two minutes as the length of videos. Each span of EEG data was cut into 1-second segments as the input. As also mentioned in the above subsection, the duration of emotion equals the duration of the session which is two minutes, longer than the segment length of one second, so the test-bed also satisfied the selecting criteria.

The two tasks selected uses different types of bio-signal, so we can verify if the lack of shift-invariance is a universal problem across bio-signal types and if the Maxblur-pooling method generalizes well to various tasks. In each task, we tested five different blur sizes ranged from 3 to 7 with the baseline using the Max-pooling layer. In the first experiment on AF detection, we also tested three different pooling factors, denoted as p and $p \in 1,2,3$, p was also conceived to be the number of pooling layers in the neural network. Therefore, we tested three p-layer CNNs to find out how the effect of Maxblur-pooling was influenced by the pooling factor p.

2.3 Evaluation Metrics

The classification accuracy on the overall dataset (including overlapped and non-overlapped segments) integrated the evaluation of how well the model performed to make a correct estimation as well as how much stable the model is. But the overall accuracy failed to make a trade-off between the two aspects. Zhang (Zhang, 2019) stated that the Maxblur-pooling could improve the shift-invariance of a neural network but may sacrifice accuracy. As a fact, he surprisingly found that both accuracy and shift-invariance are improved on the task of image classification and image generation. For the purpose of the validation, we also have to evaluate the two aspects separately. We defined the accuracy and consistency as follows to evaluate the preciseness and shift-invariance of a model. The accuracy is calculated based on the test dataset in which all the segments are not overlapped with each other. The consistency is defined based on shifted segments with an overlap less than $L-1$ between two adjacent segments that have the same label (L equals to the segment length).

The average value of both metrics are calculated with 5-fold cross-validation. Higher accuracy indicates a more accurate diagnose and higher consistency indicates more shift-invariance.

Accuracy. Classification accuracy is defined as the proportion of correct predictions to the total number of predictions, denoting the predictions as a vector $p = (p_1, p_2, p_3, ..., p_n)^T = (f(x_1), f(x_2), f(x_3), ..., f(x_n))^T$ and the ground truth as $y = (y_1, y_2, y_3, ..., y_n)^T$. Accuracy can be defined using the following equations:

$$\alpha_i = \begin{cases} 1, & \text{if } p_i = y_i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

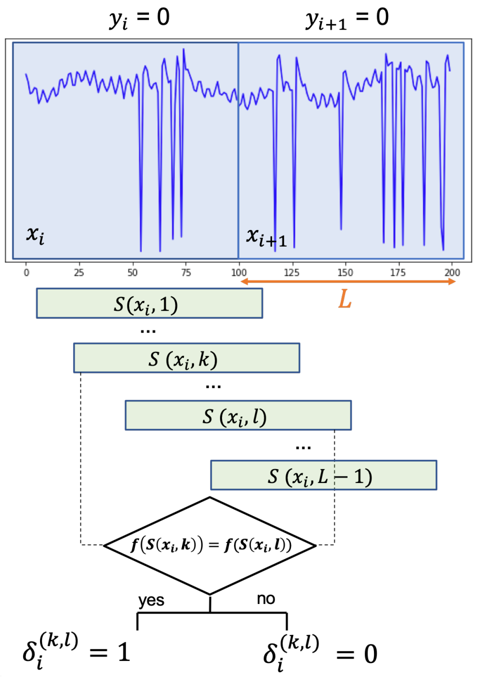
$$Accuracy = \frac{1}{n}\sum_{i=1}^{n} \alpha_i \tag{2}$$

Consistency. The consistency checks how often the network outputs the same label given the same input bio-signal segment with two different temporal shifts. For a piece of input segment, we denoted the segment length as L, then there will be $L-1$ shifts applied totally. As demonstrated in Fig. 3(a), only the segments that have the same label with its consecutively adjacent segment next in time will be used to calculate consistency. For those segments that did not have the same label with the next adjacent segment, shifts will not be applied (Fig. 3(b)). We denoted S as the temporal shift function, and $S(x,k)$ means temporally shift the input x by an offset equals to k. The consistency can be defined as follows:

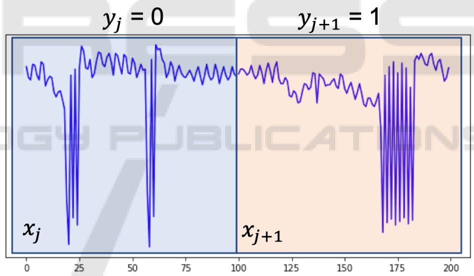
$$\delta_i^{(k,l)} = \begin{cases} 1, & \text{if } f(S(x_i,k)) = f(S((x_i,l)) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$\delta_i = \begin{cases} \frac{1}{C_{L-1}^2} \sum_{k,l \in \{1,...,L-1\}, k<l} \delta_i^{(k,l)}, & y_i = y_{i+1} \\ 0, & y_i \neq y_{i+1} \end{cases} \tag{4}$$

$$Consistency = \frac{1}{n-1}\sum_{i=1}^{n-1} \delta_i \tag{5}$$



(a) For the segment that had the same label with its next adjacent segment, shifts will be applied and consistency is calculated.



(b) For the segment that didn't have the same label with its next adjacent segment, shifts will not be applied.

Figure 3: Calculation of the consistency.

3 VALIDATION ON ATRIAL FIBRILLATION (AF) DETECTION

3.1 Tested models

For the model structure, we adopted the basic convolutional neural network (CNN) as is shown in Fig. 4. The unit block of the CNN consisted of a convolution layer, a batch normalization layer, a ReLU activation layer, and a pooling layer. The unit block will repeat for p times, which equals to the pooling factor, and we tested six variations of the pooling layers including one baseline and Maxblur-pooling with five blur sizes for comparison.

The input of the model is a 100 R-R intervals sequence. Thanks to the contributors of the dataset (Moody, 1983), we can calculate the R-R intervals from the manually annotated heart rhythm without pre-processing. The output of the model is a binary value (0 or 1) indicating the presence or absence of atrial fibrillation. We tested five different blur sizes of Maxblur-pooling ranged from 3 to 7 together with the baseline using Max-pooling. We also tested three

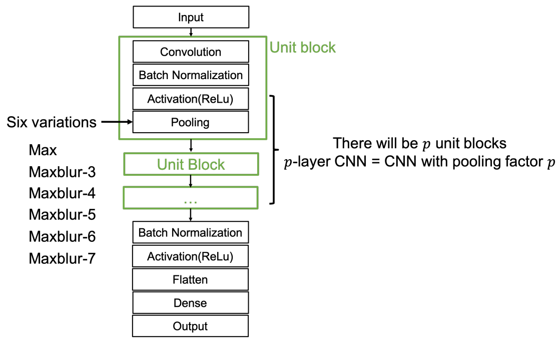


Figure 4: The structure of Convolution Neural Network (CNN).

different pooling factors to find out how the effect of Maxblur-pooling was influenced by the pooling factor.

3.2 Results and Discussion

We were able to reveal that the lack of temporal shift-invariance also exists in modern neural networks in the task of AF detection. As the example showed in Fig. 1, we observed that outputs of the baseline model using Max-pooling suffered from drastic changes as the input shifted. By using the Maxblur-pooling, this vibration of output had been significantly reduced.

The comparison results of CNN structures across pooling factors were summarized in Table.1. To demonstrate it more intuitively as shown in Fig. 5, the upper right of the figure indicates better performance on both metrics. We observed that all the models using Maxblur-pooling with different blur sizes improved consistency with various degrees compared to the baseline of Max-pooling, but improvement in accuracy was only observed with the blur size of 7 considering all the pooling factors.

For CNN with one layer, Maxblur-pooling with blur size equaling to 7 obtained best results, which improved accuracy by 1.72% and consistency by 7.94% compared to Max-pooling.

For CNN with two layers, Maxblur-pooling with blur size equaling to 7 obtained best results, improving accuracy by 6.02% and consistency by 17.92% compared to Max-pooling.

For CNN with three layers, Maxblur-pooling with blur size equaling to 5 obtained best results, improving accuracy by 12.79% and consistency by 15.36% compared to Max-pooling.

In the task of AF detection, we have observed that Maxblur-pooling did improve accuracy and consistency compared to Max-pooling. Although the best performing filter varied by the pooling factor p, we did not find there is a relationship between them. Empirically, we recommend using the blur size of 7 because it both improved accuracy and consistency in all the three CNNs with different pooling factor.

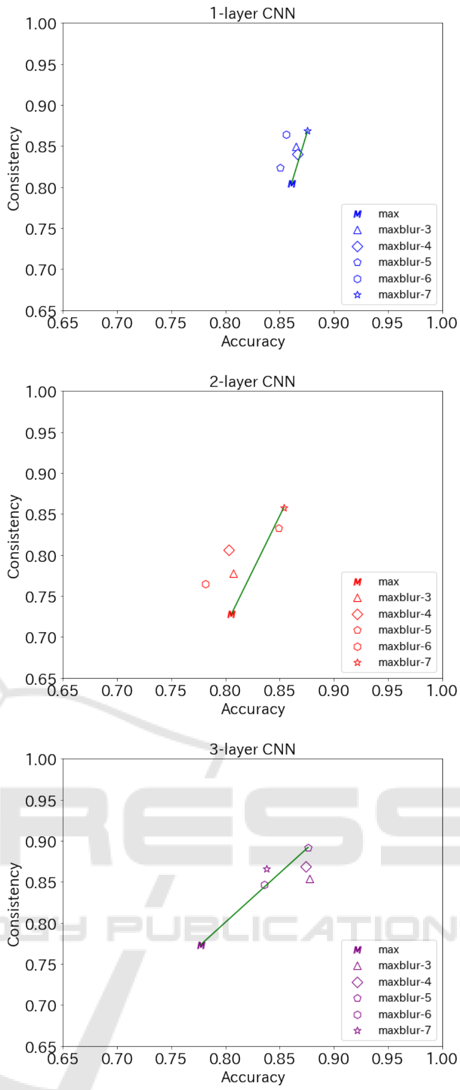


Figure 5: **Performance of models for AF detection.** In each figure, the upper right indicates better performance on both metrics. Points are plotted with different shapes corresponding to the variants of the networks using Maxblur-pooling. The number of edges equals to the blur size (triangle means Maxblur-pooling with blur size of 3). Specially, star mark represents Maxblur-pooling with blur size of 7 and the alphabet M represents the baseline of Max-pooling.

Next, we discussed the relationship between the improvement of Maxblur-pooling and how many times the Maxblur-pooling was applied. As showed in Fig. 6, when the pooling factor increased, improvements in accuracy and consistency also increased. Specifically, improvements of consistency in three-layer CNN was significantly greater than that in one

Table 1: Comparison between CNNs using different pooling layers for AF detection (accuracy and consistency are in %).

Task	Pooling Layer	1-layer CNN		2-layer CNN		3-layer CNN	
		accuracy	consistency	accuracy	consistency	accuracy	consistey
AF Detection	Max	86.11	80.44	80.54	72.76	77.70	77.32
	Maxblur-3	86.54	84.91	80.75	77.80	87.78	85.39
	Maxblur-4	86.66	84.05	80.29	80.66	87.43	86.88
	Maxblur-5	85.05	82.41	84.88	83.32	**87.64**	**89.20**
	Maxblur-6	85.61	86.42	78.14	76.47	83.60	84.65
	Maxblur-7	**87.59**	**86.83**	**85.39**	**85.80**	83.83	86.60

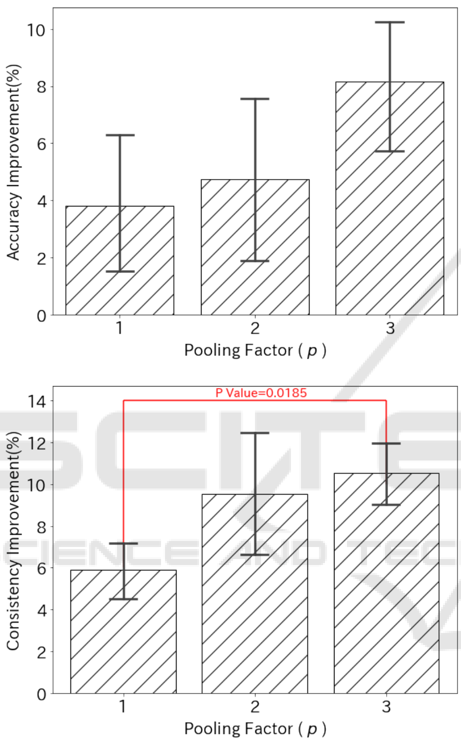


Figure 6: **Improvements of Maxblur-pooling with different pooling factors compared to the baseline.** We compared how much improvement was made by using Maxblur-pooling from the baseline of Max-pooling between different pooling factors. Tukey's multiple comparison test was employed to check the significant difference (P value$<$0.05).

layer CNN, but a significant difference in improvements of accuracy was not observed. Although the number of pooling layers needed parameter-tuning and is depended on the task and data. If shift-invariance is especially desired, we suggest employing Maxblur-pooling in a deeper network with more pooling layers.

4 EMOTION RECOGNITION ON SEED_IV EEG DATASET

4.1 Data Description

In the previous section, we discovered and discussed that the problem of shift-variance exists in AF detection 1-dimensional RRI data, and tested whether the Maxblur-pooling layer will solve the problem by replacing the traditional Max-pooling layer. We believed that the shift-variance problem should also exist in the recognition of 2-dimensional physiological signals. Among many kinds of physiological signals, we found Electroencephalography (EEG) signals are one suitable type of 2-dimensional signal. This is because EEG signals are usually measured by multiple channels; hence, there are the time dimension and the channel dimension in EEG data. EEG signals also have different characteristics than RRI data, for example, EEG signals contain a wide frequency range from 1 Hz to at least 100 Hz. Previous studies on neural science have discovered that different frequency ranges of EEG show respective properties of brain activities (Henry, 2006). Therefore, recognition tasks on EEG require the model to capture information of a wide range of frequencies.

Furthermore, the application of CNN in various kinds of recognition from EEG signals has been a widely investigated topic so that it will be meaningful to verify the effectiveness of the Maxblur-pooling layers. The deep learning models of CNN have been applied to the detection of seizure from single EEG signals (Acharya et al., 2018), emotion recognition (Zheng and Lu, 2015; Mei and Xu, 2017) and limb motion recognition (Zhang et al., 2018) from multi-channel EEG, combined with feature extraction methods or other deep learning model architecture like Recurrent Neural Network (RNN) and long short-term memory (LSTM) units. In Zhang's research, the Maxblur-pooling layers were originally proposed to

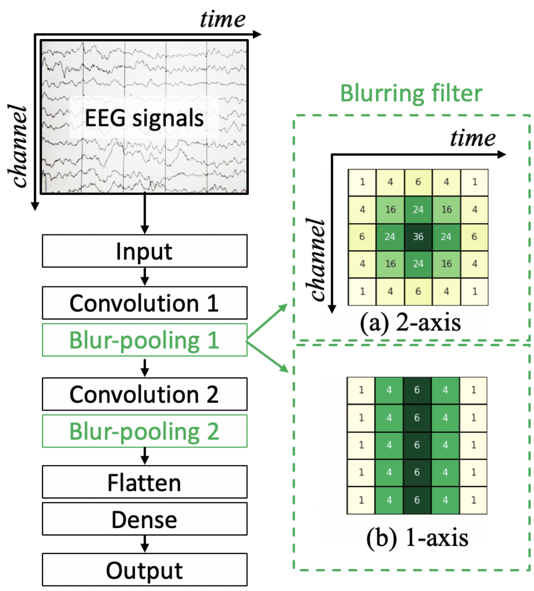


Figure 7: The architecture of the CNN model used for the emotion recognition task. Two types of blur filters are also illustrated. The horizontal axis represents the time series, and the vertical represents channels. Here blur filters of size 5 are taken as examples. (a) is the 2-axis blur filter that has a blurring effect on both temporal and channel axes, while (b) is of 1 axis that only has a blurring effect on the temporal axis.

solve the shift-variance problem of 2D images, and the 2D blur filters were proved to be effective against shift-variance of image recognition (Zhang, 2019). Therefore we anticipate that the Maxblur-pooling layers in 2-dimensional CNN will also improve the shift-invariance of the CNN models on 2-dimensional EEG data.

To verify this hypothesis, we adopted the public SEED_IV Emotion Dataset (Zheng et al., 2018) for the task of discrete emotion recognition using the CNN model.

4.2 Validation Procedure

Overall, we performed 5-fold cross-validation on each participant, which means that the recognition is participant-dependent. In the validation process on EEG data, we used 1-second segments of EEG raw data as the input to the CNN networks, which was proved feasible by previous research (Yanagimoto and Sugimoto, 2016). Hence the input shape of the network is $(62, 200)$, where 62 is the number of channels, and 200 is the total time frames of 1-second segments. The reason that we did not use any frequency-domain feature extraction method as in most previous researches (Zheng et al., 2018) is that we needed to keep the input data in the time domain in order to verify the temporal shifting effect of Maxblur-pooling layers.

As for the model architecture, we adopted a CNN model structure of 2 convolution layers, which was a simple modified version based on previous researches of emotion recognition using CNN from EEG (Mei and Xu, 2017; Moon et al., 2018). The general architecture is illustrated in Fig. 7, where the numbers of filters of the two convolutional layers are 16 and 32, and the kernel size is $(3, 3)$.The baseline model structure is the same with normal Max-pooling layers replacing the Maxblur-pooling layers.

Unlike image classification tasks, where the two axes of a 2D image represent the same meaning, the time axis and channel axis of EEG data include different information. We intend to find out whether Maxblur-pooling layers will make improvements by blurring along both time and channel axis, or only along the time axis. Therefore we tested Maxblur-pooling layers with two kinds of blur filters, as are shown in Fig. 7 as filter (a) and (b). One has a blurring effect on both time and channel axes, and the other only blurs along the time axis, which is similar to 1D blur filter. blur filter sizes of 3, 4, 5, 6, and 7, respectively of the two types of blur filters were tested.

4.3 Results and Discussion

The validation procedure was still in process, and the following results are based on data of 5 participants among all 15 in the SEED_IV dataset. The results of mean accuracy and consistency are listed in Table.2. For the comparison between two types of 2D blur filters, it was clear that 2-axis blurring outperformed 1-axis blurring. The average accuracy and consistency of 2-axis blurring of size from 3 to 7 were higher by 2.14% and 3.22% respectively than 1-axis blurring. This shows that the blur filter on the channel axis improved the recognition performance.

However, the best performance was gained by the baseline model utilized Max-pooling layers, reached an accuracy of 79.98% and consistency of 89.73%, outperformed all the models with Maxblur-pooling layers. On the contrary to our hypothesis, the application of Maxblur-pooling in this task caused recognition accuracy to drop about 6.28%, and consistency dropped about 2.53% on average. These results showed that the Maxblur-pooling layers performed badly when processing EEG signals compared to RRI, both accuracy-wise and consistency-wise. One possible reason for this outcome we speculate is that the filters in the Maxblur-pooling layers may have excluded some information contained in EEG signals

Table 2: Mean accuracy(%) and consistency(%) of two blur filters of the task of emotion recognition using EEG.

Pooling Layer				
Max	accuracy **79.98** consistency **89.73**			
	2-axis blurring		1-axis blurring	
	accuracy	consistency	accuracy	consistency
Maxblur-3	76.33	88.61	75.86	85.19
Maxblur-4	76.15	88.59	73.09	85.94
Maxblur-5	74.94	88.31	72.31	84.31
Maxblur-6	74.58	88.66	71.04	86.78
Maxblur-7	74.05	89.69	68.67	85.92

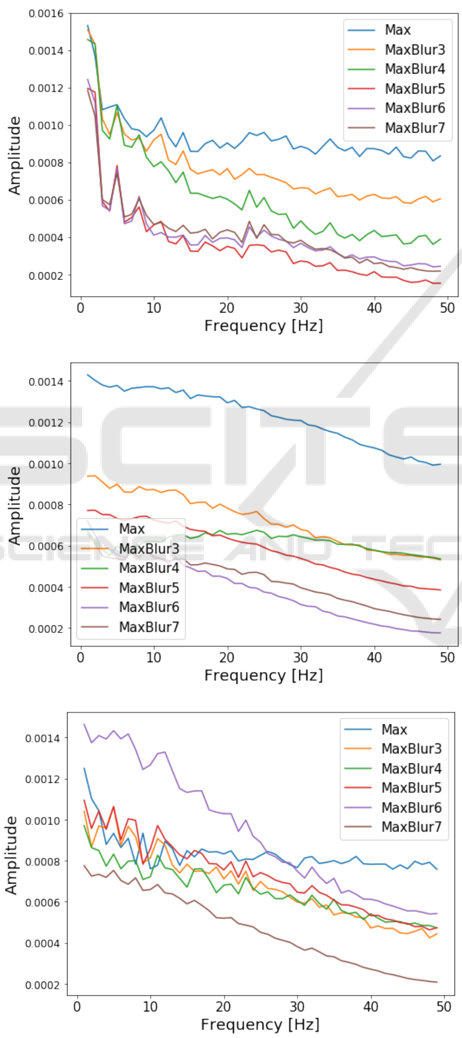


Figure 8: The FFT distribution of pooling layers' output feature. Three typical patterns are chosen.

that is important to emotions. This is because that, as mentioned earlier, EEG signals cover a wide range of frequencies, especially the gamma band (30-100 Hz) of which is crucial to emotion recognition, according to previous research (Li and Lu, 2009). However, since the blur filters also served as low-pass filters, the reason for the low accuracy was considered to be the fact that the Maxblur-pooling layers filtered out the relatively high frequency components which contained important information for emotion estimating, while Max-pooling layers maintained those information. Therefore applying Maxblur-pooling layers caused the accuracy to drop compared to Max-pooling.

To verify the theory, we pulled out the output matrices of the first pooling layer in the CNN networks from individual test samples, and conducted FFT along the temporal axis to compare the frequency distribution between normal Max-pooling layers and Maxblur-pooling layers. Although the FFT distribution of the Maxblur-pooling features cannot fully represent the actual frequencies of EEG signals, we can interpret the amplitude values as the amount of energy and information. The outcomes of some typical patterns are illustrated in Fig. 8. We noticed that among the most of FFT distribution of test samples, the amplitude values of Max-pooling are the highest in the 30-50 Hz frequency range, while values of Maxblur-pooling of larger sizes tend to be lower. This gives us the indication that the Maxblur-pooling layers filtered out more information contained in high frequencies of EEG signals compared to Max-pooling layers. As a result, the accuracy with Maxblur-pooling layers dropped, and in the meantime, the consistency was not improved.

5 GENERAL DISCUSSION

In the validation on AF detection task, we discussed that the improvements of consistency in CNN with more layers were significantly more than that in CNN with fewer layers, but a significant difference in improvements of accuracy was not observed, suggesting that deeper neural networks could be employed to gain consistency.

Table 3: Compare between CNNs using different pooling layers for AF detection **with data augmentation** (accuracy and consistency are in %).

Task	Pooling Layer	1-layer CNN		2-layer CNN		3-layer CNN	
		accuracy	consistency	accuracy	consistency	accuracy	consistey
AF Detection	Max	90.89	**98.34**	94.15	**97.53**	91.53	**97.20**
	Maxblur-3	91.91	97.40	92.49	95.33	94.37	95.00
	Maxblur-4	**92.42**	97.01	93.62	93.91	94.28	95.94
	Maxblur-5	89.15	95.57	**94.69**	95.13	94.42	95.66
	Maxblur-6	91.74	97.25	93.07	96.84	**94.57**	95.60
	Maxblur-7	90.28	97.39	94.03	96.84	92.28	96.49

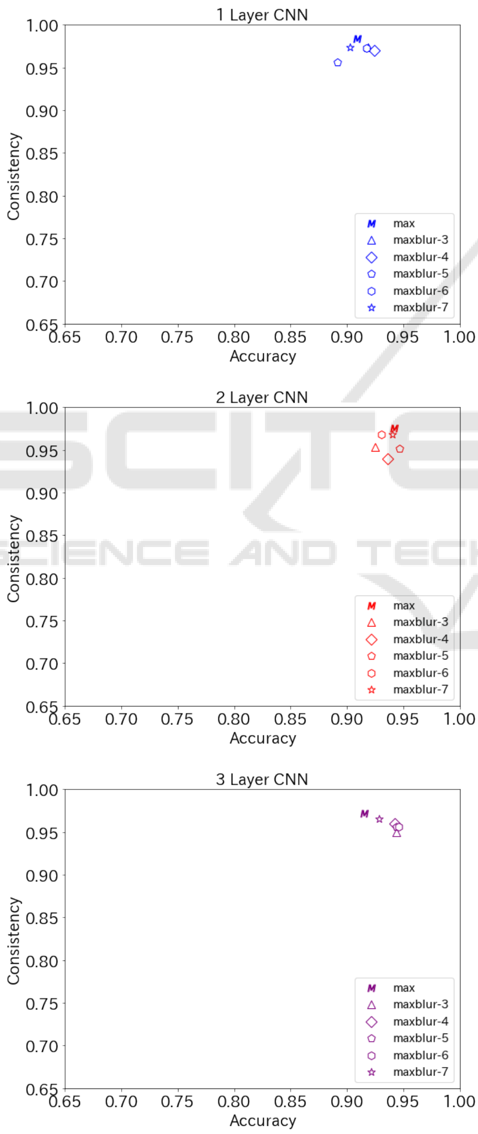


Figure 9: Results for AF detection using data augmentation. We did not observe improvements.

In the validation on emotion recognition task, Maxblur-pooling lost its advantage when applied to EEG signals. We discussed the reason was to be that the Maxblur-pooling layers filtered out the important high-frequency components while normal Max-pooling layers didn't. Therefore applying Maxblur-pooling layers caused the accuracy and consistency to drop, indicating that this method is not suitable for such tasks.

Before the method of Maxblur-pooling was proposed, researchers usually use data augmentation to gain shift-invariance. We compared the Maxblur-pooling and baselines in the task of AF detection with data augmentation to verify if Maxblur-pooling can make improvements as well when the data was augmented. As the result shown in Fig. 9, Using Maxblur-pooling made no improvements in accuracy and consistency from the baseline when applied with data augmentation (Refer to Table.3 for details). We considered the reason was that there left little room to be improved within the task of AF detection. The performance of the baseline model using Max-pooling with data augmentation already reached an accuracy of 94% and consistency of 98%. In other tasks that could not gain high accuracy with data augmentation, it's worth trying Maxblur-pooling. Maxblur-pooling could also exert its effect when data augmentation is not possible in some online learning systems.

6 CONCLUSION

The objective of this work is to verify if the problem of lacking shift-invariance also happens in neural networks that applied to bio-signals processing, and to validate the effect of Maxblur-pooling methodology in this field.

We succeeded to validate the lacking of shift-invariance that also happens in modern neural networks applied in bio-signal processing. Besides, we verified that the Maxblur-pooling method improved accuracy and consistency in the task of AF detection using RRI signal, but failed in the task of emotion recognition using the EEG signal. In the tasks that are similar to AF detection with RRI sequence as the input signal, the results obtained indicate that Maxblur-pooling, with a blur size of 7, should be used instead of max-pooling. Moreover, if shift-invariance is especially desired, deeper networks with more Maxblur-pooling is better. On the other hand, in the tasks where high-frequency components are important, we recommend to use the normal max-pooling layer. Future work is to customize the Maxblur-pooling in a way that is friendly to process bio-signals such as using the Avitzky-Golay filter instead of the Gaussian filter.

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