Collaborative General Purpose Convolutional Neural Networks

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Abstract Recently, deep neural networks (DNNs) have made outstanding progress and have been applied for solving various real-world problems. Among DNNs, convolutional neural networks (CNNs) are especially well known for their high performance as image classifiers. In this study, we generalize the CNN as a general classifier, propose a collaborative framework for neural networks and humans, and test the proposed collaborative model for medical diagnosis problems. Here, the CNN is not used as a stand-alone classifier but as a recommendation system, while humans make the final decision intuitively. To make this idea possible, a high-dimensional sample is first converted into a two-dimensional topological map before being subsequently given to the CNN as an input. The conversion of a general high-dimensional sample to a two-dimensional map allows the CNN to process it as an input while giving intuitive visual information for humans to be used in the final decision making. In this study, we attempt to expand the usage of CNNs for non-image inputs and propose a collaboration system for human and neural networks with the primary objectives of generating viable synergy between humans and AI. The paper is supported by some preliminary experiments to show the viability of our idea.

Keywords: deep neural network, convolutional neural network, self-organizing map, collaborative system, visualization

1. Introduction

Recently, deep neural networks (DNNs) [1], [2], [3], [4], and hierarchical neural networks composed of many hidden layers have been proposed and have dramatically improved the performance of machine learning in many fields. While many DNN models have been developed over some years, the very first breakthrough was the application of one of the DNN models, the convolutional neural networks (CNNs), to almost half the error rate of object recognition [5]. Since then, DNNs and especially CNNs have been utilized to solve many real-world problems.

One of the real-world problems in which DNNs, especially CNNs, perform dramatically well is in medical diagnosis [6, 7, 8, 9, 10, 11, 12] in that some of them were reported to be on par with human experts. The strength of the CNN is in its convolutional layer, where the correlated elements of the input are filtered so that their inherent structures can be discovered, which thus helps the neural net forming efficient internal representations that significantly improve its classification performance. Here, it is important to note that the CNN assumes the correlations between the elements of the input. For example, if the input is an image, it assumes that the nearby pixels are correlated, and if the input is a time series, it is assumed that the neighboring time elements are correlated. In its original form, it is not reasonable to apply CNN into a high-dimensional input in which the elements are independent, for example, in microarray gene expression data [13] where the elements are some signatures of DNA, which are not necessarily correlated.

In this preliminary study, our objective is to extend the CNN for general usage where the elements of the high-dimensional input are not necessarily correlated. Here, we convert a high-dimensional input into a two-dimensional topological map and utilize the map as an input to the CNN. The conversion of high-dimensional input into a two-dimensional map, and thus an image with correlated pixels, has two advantages. The former is that by converting non-image input into a two-dimensional image, it can then be given as an input to the CNN. The latter is that humans can be integrated into the decision-making process by visually observing the input and making the final decision after consulting the output of the CNN. Here, we propose a decision-making system combining
the strength of the CNN with the intuition of humans. The proposed collaborative framework is also our attempt to contribute to the field of explainable AI, in which the strength of AI is paired with accountability in explaining its decision as increasingly required in medical domains [14, 15, 16, 17, 18]. The proposed study shares similarities with the previous study in [19], where humans interactively observe histopathological images given as inputs and make the final decision. The proposed work differs significantly from this past work in that in the proposed work, the inputs are generalized to include non-image data, and hence, the usability of the collaborative system is improved. The current work also shares some similarities with the transparent classifier proposed in [20], in which the internal representation of the classifier is visualized to provide intuitive understanding to the human observer on the decision of the classifier. However, the current work significantly differs in that it includes humans in the decision-making loop.

This paper is supported by some experiments, first, to show the performance of the generalized CNN and, later, to show the viability of the collaborative system in decision making.

2. Collaborative CNN

The proposed method is named collaborative convolutional neural networks (C-CNN). Here, the neural network is trained with the high-dimensional data that were preprocessed into two-dimensional topological maps, as shown in Fig. 1. The two-dimensional map is then given to the CNN as an image input and classified conventionally. We adopt Kohonen’s self-organizing map (SOM) [21] as the topological map for this study that is self-organized as follows.

For input $X \in \mathbb{R}^d$, a best matching unit (BMU), $win$, is selected as in Eq. 1.

$$
win = \arg \min_i \|X - W_i\| \tag{1}
$$

In Eq. 1, $W_i \in \mathbb{R}^d$ is the reference vector associated with the $i$-th neuron on the map.

The reference vector is then modified according to Eq. 2.

$$
W_i(t+1) = W_i(t) + \eta(t)N(win, i, t)(X - W_i(t)) \tag{2}
$$

In Eq. 2, $N(win, i, t)$ is a neighborhood function that decreases along with the increase in the distance between the BMU and the $i$-th neuron on the map as defined in Eq. 3, while $\eta$ is the annealed learning rate defined in Eq. 4.

$$
N(win, i, t) = \exp\left(-\frac{\|P(i) - P(win)\|^2}{c(1 - \frac{t}{N})^2}\right) \tag{3}
$$

$$
\eta(t) = \eta_{init} \times \exp\left(-\frac{t}{N}\right) \tag{4}
$$

Here, $P(i)$ is the coordinate of the $i$-th neuron on the map, $c > 0$ is an empirically determined constant, $t$ is the current epoch, and $N$ is the target epoch. In Eq. 4, $\eta_{init}$ is the empirically defined initial learning rate.

The self-organization of the map as in Eq. 2 is executed for a predetermined epoch. After the termination, given an input $X$, the $i$-th neuron on the map generates an output $h_i$ as in Eq. 5.

$$
h_i = \exp\left(-\frac{\|X - W_i\|}{k^2}\right) \tag{5}
$$

In Eq. 5, $k$ is an empirically defined constant.

The outputs of all the neurons are then standardized so that $0 \leq h_i \leq 1$, with the BMU of $X$ having the output value of 1. The values are then associated with gradation in colors, as shown in Fig. 2, to generate a heatmap.

Examples of heatmaps on the 10 x 10 map for the Iris dataset are shown in Figs. 3-5. The Iris dataset consists of 150 four-dimensional samples from 3 different classes, Setosa, Virginica and Versicolor. It is generally known that Setosa is linearly separable from Virginica and Versicolor, while the last two classes are not linearly separable. These separability characteristics are reflected in the heatmaps, in that Setosa is clearly distinctive from the other two classes, while the difference between the Virginica and Versicolor heatmap appearances is less distinctive. Here, it is clear that the class signatures of the non-image data are preserved after the data are converted into heatmaps and thus allow the heatmaps to be used as inputs to train CNN. Here, the CNN is referred to as the self-organized map-CNN (SOM-CNN).

For collaborative decision making, after the learning phase, a BMU map is generated for a given input. This map shows the distribution of the BMUs over all of the data points on the map. An example of a BMU map for Iris is shown in Fig. 6. Here, a BMU is colored according to the class of the input represented by that BMU. The BMU of an input that is included in the learning data and misclassification results by the CNN are marked with $\Delta$ and colored according to the correct class to which the input belongs. The collaborative decision making is illustrated in Fig. 7. Here, for an unknown input $X$, a heatmap is created and given to the CNN as an image input, while a BMU map on which the BMU of the input is shown is also created. After the SOM-CNN predicts the class of the input, the system displays the heatmaps of some
Fig. 1 Overview of SOM-CNN

Fig. 2 Color distribution for heatmap

Fig. 3 Heatmaps for Setosa

Fig. 4 Heatmaps for Virginica
training data belonging to the class predicted by the SOM-CNN as well as those belonging to other classes. Humans may then visually utilize these heatmaps as references and the BMU map to decide whether to accept the decision of the SOM-CNN or to discard it. Humans may decide to discard the decision of the SOM-CNN if the visual appearance of the heatmap for the unknown input differs significantly from the reference heatmaps belonging to the class predicted by the SOM-CNN, and on the BMU map, the BMU of that input is located far from the BMUs of the training samples belonging to the same input. If the decision of the CNN is discarded, the input is treated as "unknown". It is important here to note that in this decision-making process, the final decision maker is human, while the role of the SOM-CNN is to generate suggestions. In critical problems such as medical diagnosis where the accountability of the classifier is imperative, a case labeled "unknown" will trigger a more careful analysis by human experts. Collaboration is made possible by the conversion of non-image high-dimensional data into topological heatmaps. The collaborative decision-making system allows the division of tasks between human and neural networks. In this study, the objective is to assign easy problems to be safely classified by a neural network while assigning challenging problems to be thoroughly analyzed by human experts.

3. Experiments

Preliminary experiments are conducted on 7 datasets obtained from UCI [22], whose configurations are shown in Table 1. Here, the generality of the SOM-CNN is evaluated with 10-fold cross-validation tests against those 7 problems. The generalization performances of the SOM-CNN are compared against stacked autoencoders (SAEs) [3], deep MLP with a rectified linear unit (ReLU) as the activation function, and a simple K-nearest neighbor classifier [23]. SAEs, ReLU-MLP and K-NN are chosen as comparisons due to their known generalization abilities, their implementability, and their reproducibility.
In the experiments, all the reference components of the reference vectors are randomly initialized within a range between 0 and 1. The initial learning rate is set to 0.1 and decreases along with the learning process. The parameter $c$ in the neighborhood function in Eq. 3 is empirically set to 8.0. Since the sizes of the datasets are different, the map sizes are manually optimized for each dataset, and the best performing map is the final result. The map sizes are determined to be 8x8 for Fertility, 11x11 for Hayesroth and Wine, 12x12 for Pima, 13x13 for Iris and Bupa, and 15x15 for Balance.

The heatmap images are generated with a size of 108x108 pixels in RGB from SOM before being applied as inputs for CNN. The target iterations are commonly set to 50 epochs.

The SOM-CNN in all the experiments has 3 convolutional layers, 3 max-pooling layers with a filter size of 5x5, 1 fully connected layer and 1 softmax layer. The dropout rate for training is set to 0.3 for Iris and Pima, 0.4 for Bupa and Wine, and 0.5 for Balance, Fertility and Hayesroth. The model is trained for 300 epochs with the batch size set to 20 using stochastic gradient descent to minimize the cross-entropy loss function with a learning rate of 0.0001. The parameters, such as the number of middle layers, neurons, epochs, and batch size, for SAEs, ReLU, and K-NN are manually optimized for all the datasets, and the best performing parameter is taken as the final result.

The results are given in Table 2, in which the best-performed classifier's error is written in bold while the worst one is in italics. This error rate is calculated from the average of 10-fold cross-validation tests. From Table 2, it can be observed that while the SOM-CNN is not always superior to other classifiers, the performance is relatively stable in that the performance is never too far from that of the best classifier. Table 3 shows the comparisons between the SOM-CNN and SAEs and ReLU-MLP given heatmap input denoted as “SOM-SAEs” and “SOM-ReLU”. In this experiment, the same heatmaps are used for the respective method for their input, and the error rate is calculated in the same way as in Table 2. SOM-CNN is superior to the other 2 methods in most cases, and hence, based on this preliminary test, we concluded that the SOM-CNN is appropriate for utilization as a base classifier for the proposed collaborative system.

An example of this collaborative decision making in classifying a four-dimensional three-classed balance dataset is shown in Fig. 8. Here, (a1) shows the input heatmap in which the predicted label is 2, while (b1) shows the BMU map, on which the input lays between label 0 and label 2, indicating the likelihood of misclassification. Here, the human user can make the final decision on whether to accept the decision of the classifier or to reject the decision by observing the position of the input’s BMU on the heatmap and further comparing the heatmap of the input with some reference heatmaps shown in (c1). In fact, this sample belongs to class 0, and there are some reference heatmaps that are similar to the input heatmap from class 0. An example with a different sample is shown in (a2), where this input is classified as class 2, while (b2) shows the BMU map. Human users may observe the BMU heatmap where the BMU of this input is placed among a cluster of other BMUs belonging to class 2, which indicates that the classification is likely to be correct. Humans may also consult some input samples belonging to the three possible classes shown in (c2). This sample belongs to class 2, and some heatmaps that are similar to the input heatmap are found from class 2.

4. Collaborative Experiments

Confirming the basic characteristics of the proposed collaborative classification, the C-CNN is then applied to real-world DNA microarray datasets obtained from the gene expression model selector [13]. Here, collaborative experiments were conducted on three datasets: Prostate Tumor, Diffuse Large B-cell Lymphoma (DLBCL), and Leukemia2. The configurations of these data are shown in Table 4.

Before evaluating the performances of C-CNN against the DNA microarray datasets, we show the validity of choosing SOM-CNN as the base classifier. Table 5 shows the comparisons between SOM-CNN and other classifiers using non-image input. It can be observed here that SAEs with the non-image input are the best classifier here. However, for constructing the collaborative system, we have to balance classification performance and human understandability.

Table 6 shows the performance of SOM-CNN against SAEs and ReLU-MLP with heatmap input, denoted by SOM-SAEs and SOM-ReLU in the table. Here, it is obvious that SOM-CNN outperforms the two classifiers on all three problems and hence reasonably can be used as the base classifier for our proposed collaborative system.

Establishing SOM-CNN as the base classifier, C-CNN is executed as follows. There were five participants for the experiments, and none had any knowl-
Table 2 Error rate (stddev)

| Data set  | SOM-CNN  | SAEs   | ReLU   | k-NN   |
|-----------|----------|--------|--------|--------|
| Iris      | 4.67(4.3)| 2.0(4.3)| 3.33(4.5)| 0.0(0.0) |
| Balance   | 4.81(3.2)| 1.8(1.3)| 2.0(1.2)| 21.3(5.3)|
| Bupa      | 33.9(9.7)| 27.5(9.7)| 27.8(7.3)| 60.8(6.2)|
| Fertility | 13.0(7.8)| 15.0(9.2)| 13.0(10.0)| 26.0(8.0)|
| Hayesroth | 21.9(12.8)| 22.7(8.9)| 37.4(17.3)| 41.6(13.6)|
| Pima      | 31.0(15.3)| 17.0(7.5)| 31.0(13.0)| 60.0(15.5)|
| Wine      | 2.25(2.8)| 0.55(1.7)| 1.70(3.6)| 56.5(5.6)|

Fig. 8 Example of decision making for the Balance dataset

Table 3 Error rate using SOM heatmaps

| Dataset   | SOM-CNN  | SOM-SAEs | SOM-ReLU |
|-----------|----------|----------|----------|
| Iris      | 4.67(4.3)| 6.0(6.8) | 6.0(5.5) |
| Balance   | 4.81(3.2)| 4.48(2.0)| 4.0(1.6) |
| Bupa      | 33.9(9.7)| 40.5(8.1)| 41.7(8.0)|
| Fertility | 13.0(7.8)| 18.0(15.4)| 23.0(15.5)|
| Hayesroth | 21.9(12.8)| 29.7(22.8)| 19.0(12.4)|
| Pima      | 31.0(15.3)| 33.5(14.2)| 37.5(10.5)|
| Wine      | 2.25(2.8)| 2.81(2.8)| 2.81(2.8)|

Table 4 Configuration of DNA microarray datasets

| Data set    | Size | Dim | Class | Class distribution (%) |
|-------------|------|-----|-------|------------------------|
| Prostate Tumor | 102  | 10509 | 2     | 51.0, 49.0             |
| DLBCL       | 77   | 5469 | 2     | 75.3, 24.7             |
| Leukemia2   | 72   | 11225| 3     | 38.9, 33.3, 27.8       |

edge of medical analysis. Here, similar to the previous experiments, after the SOM-CNN generates its classification output, a BMU map and 30 randomly selected heatmaps from the training data are displayed to the participants. Each participant is then allowed to accept or reject the output of the SOM-CNN. A rejected output is treated as “do not know”. In a real clinical setting, rejection indicates the necessity for a thorough clinical diagnosis by human experts. Figure 9 is an example of the questionnaire distributed to participants. Here, (a)(b)(c) show the 30 randomly selected heatmaps of the training data together with the output of the softmax layer and the decision of the SOM-CNN, in which the misclassified training data are highlighted with a yellow background, while the
Fig. 9 Questionnaire for collaborative decision making

BMU maps are shown at the bottom of (c). Finally, (d) shows the heatmap of the input to be classified together with the output of the softmax layer of SOM-CNN and the decision box in which humans may accept or reject the classification decision of the SOM-CNN. Here, humans are not allowed to modify the decision of the SOM-CNN. Here, the map sizes are set to 10x10 for SOM, and the dropout rate for CNN is set to 0.5. Other setups for SOM and SOM-CNN are the same as in the previous experiments.

\[
err = \frac{\text{miscls}}{\text{accp}} \times 100\% \quad (6)
\]

The error rate for C-CNN, \(err\), is defined in Eq. 6, where \(\text{miscls}\) denotes the number of misclassified inputs, while \(\text{accp}\) denotes the number of accepted data points.

### Table 6 SOM classifiers: error rate (stddev)

| Dataset     | SOM-CNN | SOM-SAEs | SOM-ReLU |
|-------------|---------|----------|----------|
| Prost. Tumor| 18.9(9.5) | 25.7(11.7) | 25.5(12.8) |
| DLBCL       | 8.8(11.3) | 11.3(11.8) | 13.8(11.8) |
| Leukemia2   | 12.7(13.5) | 14.1(16.9) | 15.5(23.0) |

In this collaborative experiment, the error rates for C-CNN, calculated on 10-fold-cross-validation tests, are shown in Tab. 7. In this table, "Individual C-CNN" shows the average error rates of C-CNN based on individual rejections, while "Majority C-CNN" is based on the rejection by voting, in that decisions of the SOM-CNN that are rejected by the majority of the participants are excluded.

To further analyze the performance of C-CNN, we define a difficult problem as a problem that is commonly misclassified by different classifiers. Here, as our base classifier is SOM-CNN and the strongest classifier in this study is SAEs with non-image input, these two classifiers are used for defining the difficulty of an input, as illustrated in the Venn diagram in Fig. 10.

In Table 8, "discarded rate" indicates the ratio of the discarded inputs to the total number of inputs due to the human rejections, while "overlapping rate" shows the ratio between the intersection between the three sets and the "difficult problem" area. A high overlapping rate indicates that many difficult problems are excluded. Table 8 shows that for all three problems, half of the difficult problems can be discarded due to human selection.

### Table 8 C-CNN vs SAEs

| Dataset     | discarded rate | overlapped rate |
|-------------|----------------|-----------------|
| Prost. Tumor| 21.6%          | 50%             |
| DLBCL       | 11.7%          | 50%             |
| Leukemia2   | 20.8%          | 50%             |

5. Conclusion

In this study, we proposed a framework for applying CNN for general high-dimensional data without assuming the correlations between the data’s elements by converting the general high-dimensional data into two-dimensional topological heatmaps. The preservation of the topological signatures of the data, in which
similar samples are mapped into adjacent areas on the map, generates spatial correlations for the map, and hence, it can be processed as an image by the CNN. We then expand the generality of the SOM-CNN into a collaborative decision-making framework, where human and SOM-CNN collaborated in decision making. The collaborative system is then applied to real-world medical diagnosis problems. In the experiments, we report on the preliminary results for the collaborative systems, in which we first demonstrated that the selection of SOM-CNN as the base classifier is justified. We then showed that human intuitiveness is efficient in filtering problems that are potentially hard to classify by neural networks. In this preliminary study, we limited our experimental scope to exclude difficult problems that are likely to be misclassified without allowing human experts to modify the decision of the neural network. As immediate future works, we will allow human experts to modify the decision of the neural networks regarding discarded input. In real-world clinical settings, our proposed collaborative system can be useful as a collaborative system where the neural network classifies easy problems by collaborating with humans that are not necessarily experts in the given task while assigning difficult problems to human experts. It is interesting to also notice that majority voting by nonexperts results in better performance compared to individual rejection. As one of the future works, we will explore this point further. We are aware that the intuitive selection or rejection of a certain input by humans does not offer an explanation of the causality between the input and the decision. However, it may lead to a “selected explanation” in which human experts do not need to explain all decisions and thus can concentrate on challenging problems.

In this paper, we reported on clinical data, but the framework can also be utilized for industrial, educational and other real-world problems, which will be our immediate future work along with the development of a better interface for ensuring better collaboration between human and neural networks.

References

[1] Y. Bengio, P. Lamblin, D. Popovici and H. Larochelle: Greedy layer-wise training of deep networks, Proc. Advances in Neural Information Processing Systems, Vol.19, pp.153–160, 2006.
[2] G. E. Hinton, S. Osindero and Y. -W. Teh: A fast learning algorithm for deep belief nets, Neural Comp., Vol.18, pp.1527–1554, 2006.
[3] G. E. Hinton and R. R. Salakhutdinov: Reducing the dimensionality of data with neural networks, Science, Vol.313, No. 5786, pp. 504-507, 2006.
[4] Y. LeCun, Y. Bengio and G. Hinton: Deep learning, Nature, Vol.521, pp.436–444, 2015. https://doi.org/10.1038/nature14539
[5] A. Krizhevsky, I. Sutskever and G. E. Hinton: Imagenet classification with deep convolutional neural networks, Advances in Neural Information Processing Systems, pp.1097-1105, 2012.
[6] G.Litjens, C. Sánchez, N. Timofeeva et al.: Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis, Sci. Rep., Vol.6, No.26286, 2016. https://doi.org/10.1038/srep26286
[7] D. Ravi et al.: Deep learning for health informatics, IEEE Journal of Biomedical and Health Informatics, Vol.21, No.1, pp.4-21, 2017.
[8] A. Esteva, B. Kuprel, R. Novoa et al.: Dermatologist-level classification of skin cancer with deep neural networks, Nature, Vol.542, pp.115–118, 2017. https://doi.org/10.1038/nature21056
[9] J. Xie, R. Liu, I. Luttrell, C. Zhang et al.: Deep learning based analysis of histopathological images of breast cancer, Frontiers in Genetics, Vol.10, Article 80, 2019.
[10] J. Kather, C. Weis, F. Bianconi et al.: Multi-class texture analysis in colorectal cancer histology, Sci. Rep., Vol.6, pp.27098, 2016. https://doi.org/10.1038/srep27098
[11] T. Araujo, G. Aresta, E. Castro, J. Rouco, P. Aguia, C. Eloy, A. Pol’onia and A. Campilho: Classification of breast cancer histology images using convolutional neural networks, PloS One, Vol.12, No.6, e0177544, 2017.
[12] D. Komura and S. Ishikawa: Machine learning methods for histopathological image analysis, Computational and Structural Biotechnology Journal, Vol.16, pp.34-42, 2018.
[13] A. Statnikov, I. Tsamardinos, Y. Dosbayev et al.: GEMS: A system for automated cancer diagnosis and biomarker discovery from microarray gene expression data, Int. J. Med. Inf., Vol.74, pp.491–503, 2005.
[14] G. R. Vásquez-Morales, S. M. Martínez-Monterrubio, P. Moreno-Ger and J. A. Recio-Garcia: Explainable prediction of chronic renal disease in the Colombian population using neural networks and case-based reasoning, IEEE Access, Vol.7, pp.152900-152910, 2019.
[15] S. M. Lundberg, B. Nair, M.S. Vavilala et al.: Explainable machine-learning predictions for the prevention of hypoxaemia during surgery, Nat. Biomed. Eng., Vol.2, pp.749-760, 2018. https://doi.org/10.1038/s41551-018-0304-0
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