

## RESEARCH ARTICLE

# ICAN: Interpretable cross-attention network for identifying drug and target protein interactions

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**Citation:** Kurata H, Tsukiyama S (2022) ICAN: Interpretable cross-attention network for identifying drug and target protein interactions. PLoS ONE 17(10): e0276609. <https://doi.org/10.1371/journal.pone.0276609>

**Editor:** Lun Hu, Xinjiang Technical Institute of Physics and Chemistry, Chinese Academy of Sciences, CHINA

**Received:** September 5, 2022

**Accepted:** October 10, 2022

**Published:** October 24, 2022

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**Data Availability Statement:** The program is freely available at <https://github.com/kuratahiroyuki/ICAN>.

**Funding:** This work was supported by a Grant-in-Aid for Scientific Research (B) (22H03688) and partially supported by a Grant-in-Aid for JSPS Research Fellows (22J22706) from the Japan Society for the Promotion of Science (JSPS). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

## Abstract

Drug–target protein interaction (DTI) identification is fundamental for drug discovery and drug repositioning, because therapeutic drugs act on disease-causing proteins. However, the DTI identification process often requires expensive and time-consuming tasks, including biological experiments involving large numbers of candidate compounds. Thus, a variety of computation approaches have been developed. Of the many approaches available, chemogenomics feature-based methods have attracted considerable attention. These methods compute the feature descriptors of drugs and proteins as the input data to train machine and deep learning models to enable accurate prediction of unknown DTIs. In addition, attention-based learning methods have been proposed to identify and interpret DTI mechanisms. However, improvements are needed for enhancing prediction performance and DTI mechanism elucidation. To address these problems, we developed an attention-based method designated the interpretable cross-attention network (ICAN), which predicts DTIs using the Simplified Molecular Input Line Entry System of drugs and amino acid sequences of target proteins. We optimized the attention mechanism architecture by exploring the cross-attention or self-attention, attention layer depth, and selection of the context matrixes from the attention mechanism. We found that a plain attention mechanism that decodes drug-related protein context features without any protein-related drug context features effectively achieved high performance. The ICAN outperformed state-of-the-art methods in several metrics on the DAVIS dataset and first revealed with statistical significance that some weighted sites in the cross-attention weight matrix represent experimental binding sites, thus demonstrating the high interpretability of the results. The program is freely available at <https://github.com/kuratahiroyuki/ICAN>.

## Introduction

Drug–target protein interaction (DTI) identification is fundamental for drug discovery and drug repositioning, because therapeutic drugs act on disease-causing proteins. However, the DTI identification process often requires expensive and time-consuming tasks, including biological experiments involving large numbers of candidate compounds [1]. To address these

**Competing interests:** The authors have declared that no competing interests exist.

problems, intensive efforts have focused on virtual screening or computational prediction of DTIs based on large biological datasets and information available in public databases. A variety of computational approaches, including structure-based, similarity-based, and feature-based chemo-genomics methods, have been proposed for DTI prediction [2]. Conventional structure-based approaches, that include docking simulations have been studied for decades, but they are limited to proteins for which the three-dimensional structure is known or can be precisely reproduced by molecular dynamics simulations. Similarity-based approaches such as kernel regression [3–5] and matrix factorization [6–8] utilize known drug-target similarity information to infer new DTIs. However, these methods are not applicable to target proteins of different classes for which similarity information is lacking [9]. Feature-based methods used in chemo-genomics approaches compute the descriptors of drugs and proteins as the input data to train machine and deep learning models so that they can accurately predict unknown DTIs as classification models and the associated binding affinity as regression models, respectively. In the feature-based approaches of the classification models, drug compounds can be represented as types of fingerprints, including extended connected fingerprints (ECFPs) [10] and PubChem [11], one-dimensional (1D) sequences, and molecular graphs (traditionally called two-dimensional (2D) structures). Protein sequences are described as 1D sequences, which are converted into feature vectors using various descriptors, including composition transition distribution [12] and protein sequence composition (PSC) descriptors [13]. In general, machine learning methods, such as random forest and gradient boosting, can be combined with such descriptors to predict DTIs [14–18], where appropriate design and selection of descriptors are critically important [19,20]. From a different point of view, several recent studies have integrated heterogeneous, protein- or drug-related knowledge, such as GO semantic information [21], biological networks [22], and drug-drug interactions [23], into PPI datasets to improve PPI prediction performance.

Recent studies have proposed various end-to-end, deep learning frameworks that integrated sequence representation and model training in a unified architecture [24,25]. Deep learning-based methods such as deep neural network [26], autoencoder [27], long short-term memory [28,29], convolutional neural networks (CNNs) [30,31], and Transformer [13] have improved the prediction performance of machine learning methods. DeepDTI [9] proposed a deep belief network [32] that uses ECFP2, ECFP4, and ECFP6 [10] to encode drugs and PSC descriptors to encode amino acids (AAs). DeepDTA [30] uses two CNNs that extract the features of the Simplified Molecular Input Line Entry System (SMILES) of drugs and AA sequences from their label-encoding vectors. DeepConv-DTI [33] involves an architecture similar to DeepDTA, which uses CNNs with max pooling layers and fingerprint ECFP4 to encode SMILES. From another aspect in which a drug compound is regarded as a molecular graph, GNN-CPI [34] and GraphDTA [35] have implemented graph neural networks (GNNs) [36,37] and graph CNNs [38,39], respectively. These predictors separately learn the molecular representations of drugs and proteins and then concatenate their features to calculate a final output, while neglecting the interactions of sub-sequences between drugs and proteins.

Such interactions are widely considered by exploiting the attention mechanisms of Transformer, an encoder-decoder model consisting of multi-headed attention layers and pairwise feed-forward to extract sequence-to-sequence features. TransformerCPI [13] implemented a Transformer that applies drugs and proteins via a sequence-to-sequence or cross-attention mechanism. MolTrans [40] employs two self-attention mechanisms to create an interaction map that integrates the separately generated context features from drugs and proteins. These attention-based methods have suggested a few examples that roughly explain how a high value of attention weight matrixes correspond to experimental binding sites, but they do not prove this in an objective and statistical manner.

To overcome these problems, we developed a new attention-based method that predicts DTIs based on SMILES of drugs and AA sequences of proteins; this method was designated the interpretable cross-attention network (ICAN). We optimized the attention mechanism architectures in terms of cross-attention or self-attention, attention layer depth, and selection of the context matrixes from the attention networks. ICAN outperformed state-of-the-art methods in several respects and first revealed with statistical significance that some weighted attention sites represent experimental binding sites, thus demonstrating the distinct interpretability of the method.

## Materials and methods

### Computation framework

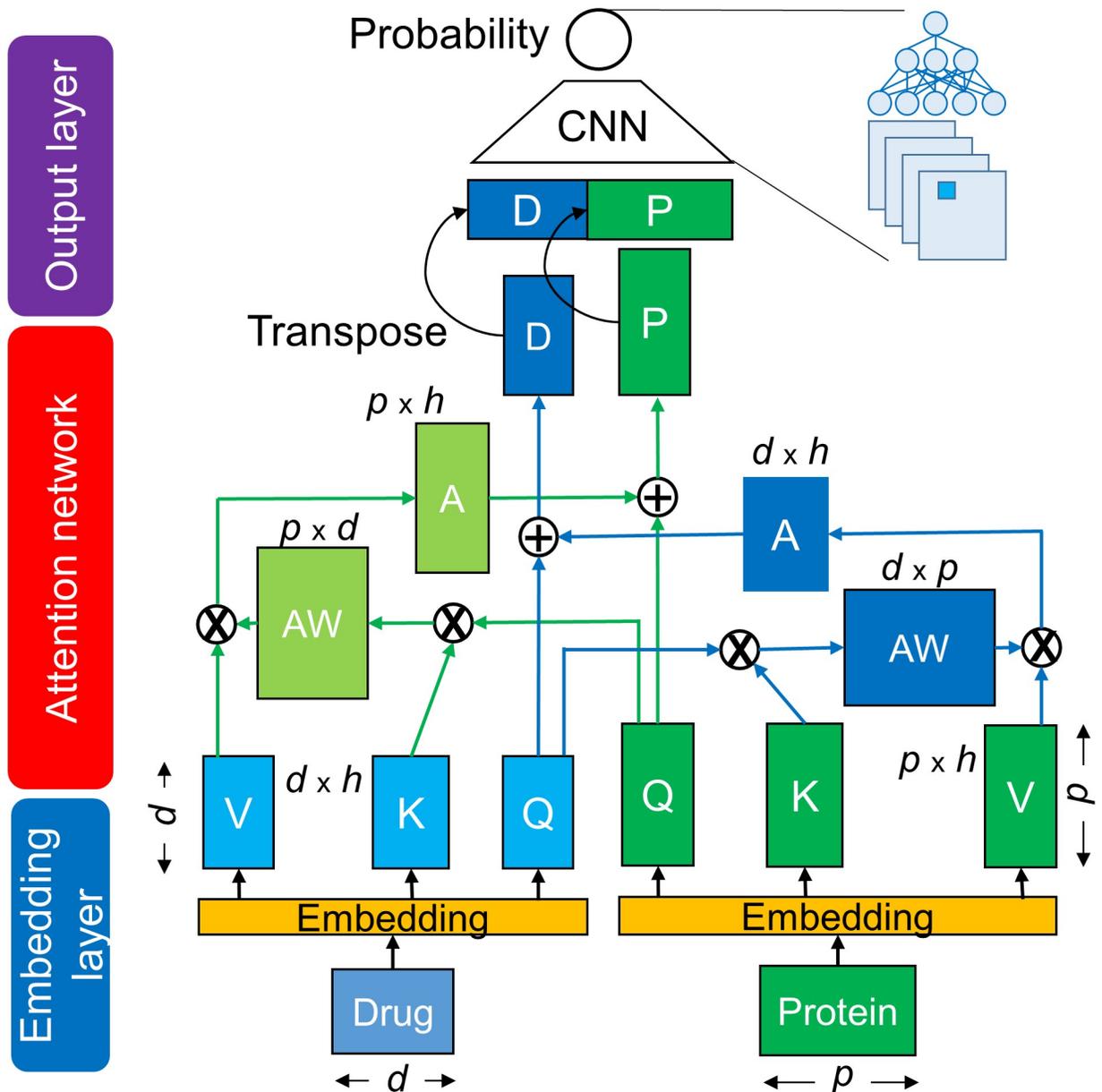
The proposed cross-attention model consists of three networks: an embedding layer, an attention layer, and an output layer, as shown in Fig 1. In the embedding layer, the SMILES of drugs and AA sequences of target proteins are separately encoded as the embedding matrixes. These matrixes are input into the cross-attention network to generate the drug-related context matrix of a protein and the protein-related context matrix of a drug. The resulting context matrixes are applied to the output layer of the CNN, which functions as a decoder to capture local feature patterns at different levels, followed by computing of a DTI probability score. The cross-attention considers sub-sequence interactions between a drug and a protein to produce the context matrixes; the CNN uses different filters to extract local sub-sequence patters within the context matrixes. Details in encoding methods and attention-based models are described in Tables 1 and 2.

### DTI dataset

The three widely used datasets were prepared: DAVIS, BindingDB, and BIOSNAP, as shown in Table 3. These were the same datasets employed in a previous study [40] and facilitated direct comparison of our proposed method with existing methods. The DAVIS dataset consists of biochemically determined experimental K<sub>d</sub> (dissociation constant) values for 68 drugs and 379 proteins [41]. The BindingDB database [42] includes K<sub>d</sub> values for 10,665 drugs and 1,413 proteins. DTI pairs with a K<sub>d</sub> < 30 μM are regarded as positive samples. The MINER DTI dataset from the BIOSNAP collection [43] includes 13,741 DTI pairs for 4,510 drugs and 2,181 proteins from DrugBank [44]. As the BIOSNAP dataset contains only positive DTI pairs, negative DTI pairs are collected and removed from among the unseen pairs [40]. We removed samples for which SMILES was not applicable to RDKit [45].

### Drug and protein representations

Drugs are represented by the SMILES [46], which is a character sequence of atoms and bonds (e.g., C, N, O, =), generated by depth-first traversal for a molecule graph. The SMILES has the disadvantage that its respective characters do not always correspond to chemically valid molecules. To overcome this problem, SELF-referencIng Embedded Strings (SELFIES) [47] are introduced so that all of the tokens or words of the SELFIES correspond to chemically valid molecules, increasing the reliability of interpretation and rationality of the learning algorithms or mechanisms. It should be noted that a token is the minimum meaningful character set. A target protein is represented as a letter sequence of the 20 standard AAs.



**Fig 1. Architecture of the cross-attention-based neural network.** It is the CA\_DP network (Table 2). Q, K, and V indicate Query, Key, and Value matrices. AW: Attention-weight matrix, A: Attention matrix, D: Drug-context matrix, P: Protein-context matrix, d: Length of drug sequence, p: Length of protein sequence, h: Hidden dimension size.

<https://doi.org/10.1371/journal.pone.0276609.g001>

### Frequent consecutive sub-sequence mining

The frequent consecutive sub-sequence (FCS) mining method [40] is used to extract sub-sequences with variable length for both drug compounds and proteins. The FCS algorithm finds recurring sub-sequences across drug and protein sequence datasets. According to the natural language processing-based identification method of sub-word tokens [48,49], FCS produces a hierarchical set of frequently occurring sub-sequences. After collecting a sequence set of SMILES and AA sequences, the FCS method decomposes or tokenizes the sequences of drugs and proteins into sub-sequences and individual atoms and AAs that are designated a

**Table 1. Drug and protein encoding methods.**

Name	Drug token	Protein token
nn.Embedding of FCS	SMILES FCS	AA FCS
nn.Embedding of SMILES	SMILES character	AA letter
nn.Embedding of SELFIES	SELFIES word	AA letter
one-hot encoding of SMILES	SMILES character	AA letter
one-hot encoding of SELFIES	SELFIES word	AA letter

“Character” and “word” indicate “a letter or a symbol” and “minimum chemically valid characters”, respectively.

<https://doi.org/10.1371/journal.pone.0276609.t001>

**Table 2. Architectures of different attention-based models.**

Method name	Attention mechanism	Attention layer depth	Context matrix	Output layer
CA_DP	Cross-attention	1	Drug+Protein	CNN
CA2_DP	Cross-attention	2	Drug+Protein	CNN
CA3_DP	Cross-attention	3	Drug+Protein	CNN
CA_DP_FCL	Cross-attention	1	Drug+Protein	FCL
SA_DP	Self-attention	1	Drug+Protein	CNN
CA_D	Cross-attention	1	Drug	CNN
CA_P (ICAN)	Cross-attention	1	Protein	CNN

All of the models employ the nn.Embedding of FCS (Table 1).

<https://doi.org/10.1371/journal.pone.0276609.t002>

token set. FCS scans the token set to identify the most-frequent consecutive tokens (e.g., X, Y) and updates them with their combined token (XY). FCS repeats the process of scanning, identification, and updating until no frequent token is above a specific threshold or the number of tokens reaches a specific threshold. Frequent sub-sequences are bound into one token, and infrequent sub-sequences are decomposed into short tokens.

## Encoding methods

We paired each token of SMILES FCS, AA FCS, SMILES, SELFIES, and AAs with its corresponding label integer to generate a label-encoding vector. The resulting label-encoding vectors were embedded into token-embedding matrixes by two encoding methods, nn.Embedding (PyTorch) and one-hot encoding. Table 1 shows the five encoding methods

**Table 3. Statistics of the employed datasets: DAVIS, BindingDB and BIOSNAP.**

Dataset	Drug	Protein	Positive sample			Negative sample		
			Train	Valid	Test	Train	Valid	Test
DAVIS	68	379	1,043	1,043	160	2,846	303	5,708
BindingDB	10,665	1,413	6,329	6,334	925	5,712	1,903	11,377
BIOSNAP	4,510	2,181	9,656	9,533	1,394	1,344	2,761	2,719

The numerical values indicate the numbers.

Positive DTI pairs were divided into training, validation, and testing sets at a ratio of 7:1:2. For well-shaped training, the number of negative DTI samples was set to the same number as positive samples in the training datasets. The remaining negative pairs were placed in the validation and test datasets. The positive and negative pairs are balanced in the BIOSNAP test dataset; they are imbalanced in the DAVIS and BindingDB test datasets, where the number of negative samples is more than 20-fold and 7-fold greater than that of positive samples, respectively.

<https://doi.org/10.1371/journal.pone.0276609.t003>

employed: (1) nn.Embedding of FCS embeds the label-encoding vectors of SMILES FCSs and AA FCSs; (2) nn.Embedding of SMILES embeds the label-encoding vectors of SMILES characters and AA letters; (3) nn.Embedding of SELFIES embeds the label-encoding vectors of SELFIES words and AA letters; (4) one-hot encoding of SMILES embeds the label-encoding vectors of SMILES characters and AA letters; and (5) one-hot encoding of SELFIES embeds the label-encoding vectors of SELFIES words and AA letters. Here, we demonstrate how to make a label encoding vector with SMILES characters. SMILES [CN = C = O] is decomposed into a character list: [C, N, =, C, =, O], which is then converted into a label-encoding vector [1, 3, 60, 1, 60, 4, 60], where (C:1, N:3, =: 60, O:4).

As drug and protein sequences have varying lengths, the maximum sizes of the label-encoding vectors for drugs and proteins were set to 50 and 545, respectively. nn.Embedding embeds the label-encoding vectors of a drug and protein into  $50 \times 384$  and  $545 \times 384$  token-embedding matrixes, respectively. The one-hot encoding method encodes a drug and a protein into  $50 \times$  (length of the SMILES character list or SELFIES word list) and  $545 \times$  (length of AA letter list) token-embedding matrixes, respectively.

We also added a positional embedding method to the token-embedding, because the position of words generally plays an essential role in any language grammar, defining the semantics of a sentence. As the token-embedding matrixes do not have any information regarding position of the sub-sequences or tokens, we added position information for the sub-sequences to their features. The position label-encoding vector is embedded by nn.Embedding into the position-embedding matrix, which is added to the token-embedding matrix. The resulting matrix was designated the embedding matrix.

## Cross-attention network

We built multi-head cross-attention networks with an attention head number of  $h$  [50]. The query of a target protein,  $Q^p = (Q_1^p, \dots, Q_h^p)$ , is provided with the embedding matrix of a protein  $Y^p$  by:

$$Q_i^p = Y^p W_i^Q (i = 1, 2, \dots, h), \quad (1)$$

where  $W_i^Q$  represents the weight matrix. The Key and Value of a drug,  $K^D = (K_1^D, \dots, K_h^D)$  and  $V^D = (V_1^D, \dots, V_h^D)$ , are provided with the embedding matrix of a drug  $Y^D$  by:

$$K_i^D = Y^D W_i^K, \quad (2)$$

and

$$V_i^D = Y^D W_i^V. \quad (3)$$

We calculated the dot product of  $Q_i^p$  and  $K_i^D$  to obtain the attention weight matrix given by:

$$Attention\ weight_i^p = softmax\left(\frac{Q_i^p K_i^D T}{\sqrt{d}}\right), \quad (4)$$

where  $d$  represents the column dimension of  $W_i^Q$  and  $K_i^D T$  represents the transposed matrix of  $K_i^D$ . The attention weight matrix is multiplied by  $V_i^D$  to compute the attention, or head, which is given by:

$$head_i^p = Attention_i^p = Attention\ weight_i^p \cdot V_i^D. \quad (5)$$

The multi-head attention is expressed by:

$$\text{Multihead}(Q^p, K^D, V^D) = \text{concat}(\text{head}_i^p, \dots, \text{head}_i^p) \cdot W_0^p. \quad (6)$$

Subsequently, context matrix of protein  $C^p$  is given by

$$C^p = Q^p + \text{Multihead}(Q^p, K^D, V^D). \quad (7)$$

Next to the context matrix of a protein, we computed the following context matrix of a drug, and vice versa.

$$C^D = Q^D + \text{Multihead}(Q^D, K^p, V^p) \quad (8)$$

The final context matrixes from the cross-attention networks have three types: consecutively concatenated context matrixes of a drug and protein ( $C^D, C^p$ ), context matrix of a drug alone  $C^D$ , and context matrix of a protein alone  $C^p$ .

The resulting context matrix was sent to the output layer to obtain a final probability or prediction score. The output layer consists of two sets of 1D-CNN, ReLU function, max pooling layer, and dropout layer, and one linear transformation layer with the sigmoid function. As an alternative output layer, we prepared fully connected layers composed of two sets of a linear transformation layer, ReLU function, and dropout layer, and one linear transformation network with the sigmoid function.

## Evaluation

Six statistical metrics were used to evaluate the prediction performance of the proposed models: sensitivity (recall) (SN), specificity (SP), precision (PR), F1, area under the receiver operating characteristic curve (ROCAUC), and area under the precision and recall curve (PRAUC) [51]. SN, SP, PR, and F1 are given by:

$$SN = \frac{TP}{TP + FN}, \quad (9)$$

$$SP = \frac{TN}{TN + FP}, \quad (10)$$

$$PR = \frac{TP}{TP + FP}, \quad (11)$$

and

$$F1 = \frac{2 \cdot PR \cdot SN}{PR + SN}, \quad (12)$$

where  $TP$ ,  $TN$ ,  $FP$ , and  $FN$  denote the numbers of true positives, true negatives, false positives, and false negatives, respectively. We conducted five independent runs to train the models and evaluate them with the test datasets. The statistical metrics were averaged over 5 models. PRAUC was an effective metric on the imbalanced test datasets of DAVIS and BindingDB, where the number of negative pairs was much larger than that of positive pairs.

## Attention site analysis

To demonstrate the interpretability of the attention mechanisms, we investigated the relationship between a high value in the attention weight matrix and the experimental drug-binding sites of target proteins or whether the attention sites correspond to the experimental DTI

binding sites. First, we added experimental data regarding drug-binding sites, as derived from sc-PDB [52], to the BIOSNAP test dataset. Consequently, we updated 160 DTIs with their binding sites. Notably, DTI samples with experimental drug-binding sites are limited. Second, we fed the 160 DTIs into the CA\_P model (Table 2) to generate attention weight matrixes, which were expanded by the protein and drug sequence axes. For each DTI sample, we sorted the attention sites according to value and then selected the top 30 attention sites. Third, we counted the attention sites that corresponded to the experimental binding sites for each target protein, and this value was designated the experimental consistency number. Fourth, to statistically validate the experimental consistency numbers, we artificially generated random binding sites for each target protein, while keeping the number of random sites the same as the number of experimental sites. We then calculated how many times the top 30 attention sites corresponded to the randomly generated binding sites, which was designated the simulated consistency number. This simulation process was iterated 10,000 times for the 160 DTIs to obtain a profile of simulated consistency numbers. Finally, based on the simulated profile, we calculated the z-score of the experimental consistency number between the top 30 attention sites and the experimental binding sites.

## Implementation

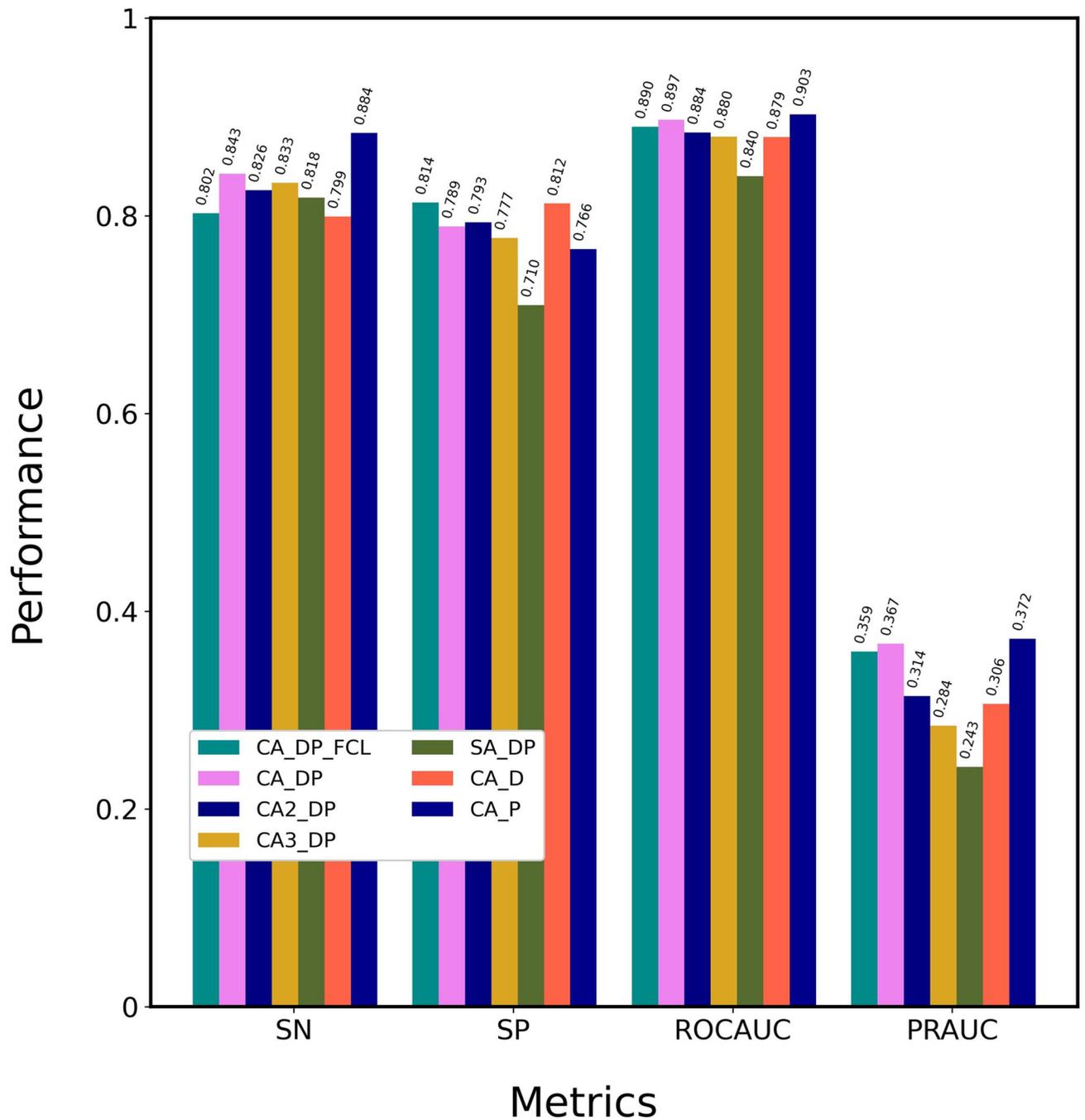
All the programs were written in Python. Programming regarding SMILES and SELFIES was written using RDKit [45]. The deep learning programs, including the attention mechanisms and CNN, were implemented in PyTorch [53].

## Results and discussion

### Optimization of neural network structures

There are a number of network architectures in the attention-based methods (Table 2). We designed or optimized the network structures of the attention-based network and output layer using the DAVIS dataset with nn.Embedding of the FCS. This optimality of this encoding will be demonstrated later. The attention mechanism selects either of two types: self-attention or cross-attention. The depth of attention layers varies as 1, 2, and 3. The context matrixes resulting from the attention network have three types of concatenated context matrixes: drug and protein, drug context alone, and protein context alone. The output layer employs either of two neural networks: CNN or fully connected layer.

First, we defined CA\_DP (Table 2, Fig 1) as the base model that consists of nn.Embedding of the FCS, one-layer cross attention mechanisms for the concatenated matrixes of drugs and proteins, and CNN output layer, and tuned its hyper-parameters. Consequently, we determined the number of multi-head attentions as 4, the learning rate as 0.001, maximum epochs as 50, and training batch size as 128. The Adam optimizer was used. All hyper-parameters are provided in our program. To select the neural network suitable for the output layer, we compared CA\_DP with CA\_DP\_FCL that used the fully connected layer as the output layer, as shown in Fig 2 and S1 Table. CNN presented higher SN, ROCAUC, and PRAUC values than FCL; thus, CNN was selected. We emphasized the values of PRAUC and ROCAUC to determine the best method, because they are independent of a threshold value, while SP, PR and F1 depend on the threshold. S1 Table indicates the values of all the six metrics including PR and F1. We considered that CNN captured local context patterns with different filters. To investigate the effect of attention layer depth on performance, we compared one layer (CA\_DP), two layers (CA2\_DP), and three layers (CA3\_DP). An increase in the layer number decreased the ROCAUC and PRAUC values, suggesting that complex attention mechanisms do not improve performance. Thus, we selected a one-layer attention mechanism. We compared the cross-



**Fig 2. Optimization of the attention-based network architecture.** Attention-based models with nn.Embedding of FCS were trained using the DAVIS training dataset and evaluated using the DAVIS test dataset. Details of the methods are shown in Table 2. CA\_P was designated ICAN.

<https://doi.org/10.1371/journal.pone.0276609.g002>

attention (CA\_DP) and self-attention (SA\_DP) mechanisms (S1 Fig). The cross-attention mechanism exhibited better performance for the four metrics than the self-attention mechanism. This suggests that interactive cross-attentions between drug and protein features are critically important for prediction. This was not consistent with the observation that the two

self-attention mechanisms employed by MolTrans exhibit high prediction performance. We speculate that MolTrans complements the lack of cross-attention between drugs and proteins with an interaction map that integrates drug and protein context features from the self-attention mechanism.

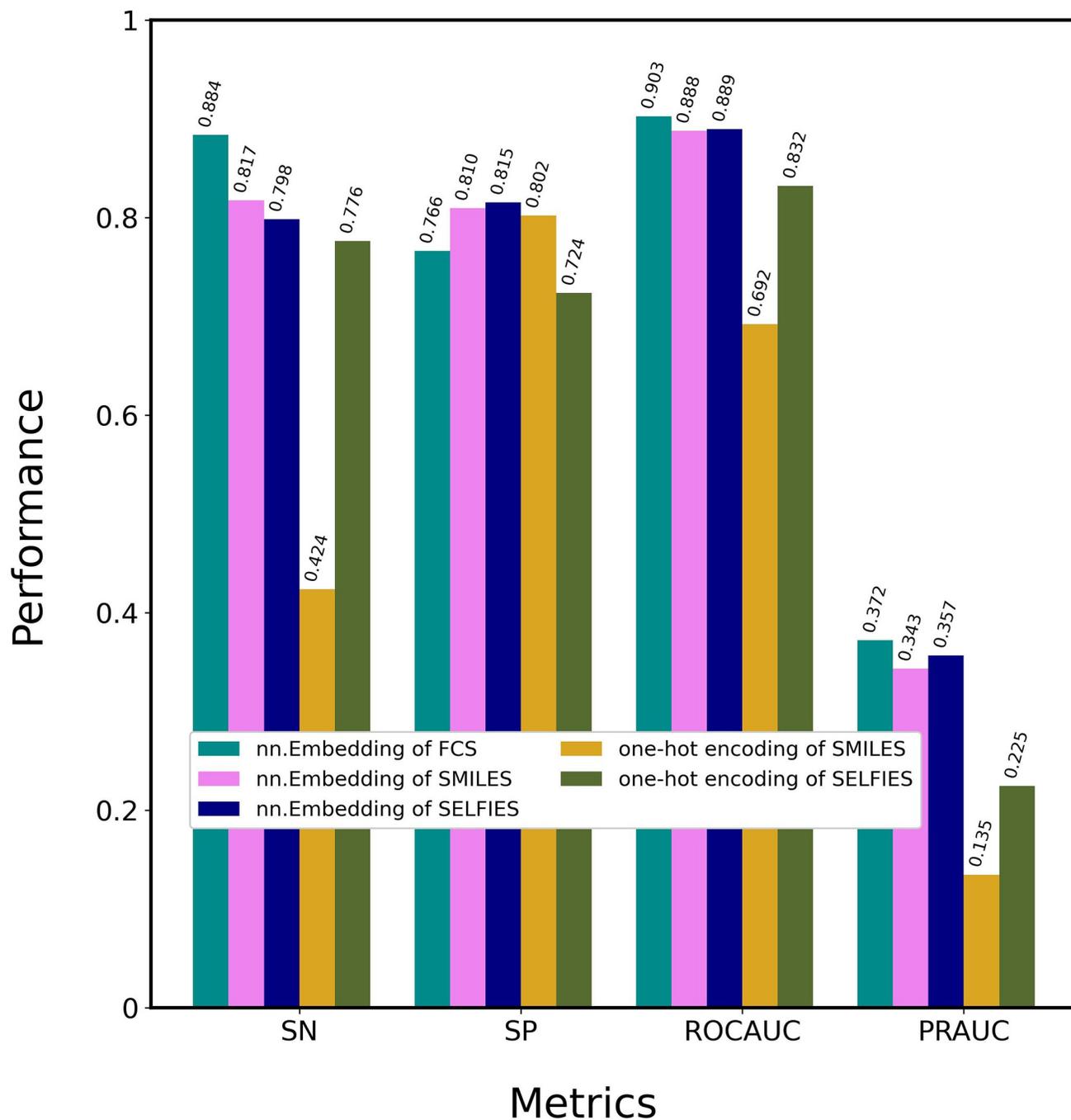
To select the optimal context matrixes resulting from the attention mechanisms, we compared CA\_DP, CA\_D, and CA\_P (S2 Fig). CA\_P provided higher SN, ROCAUC, and PRAUC values than CA\_DP and CA\_D, suggesting that CA\_P decodes drug-related protein context features without any protein-related drug context features. This is similar to TransformerCPI, which decodes protein features based on encoded drug features, whereas CA\_P uses a plain one-attention-layer architecture without any pairwise feed-forward. We conclude that the plain attention mechanism, CA\_P, is sufficiently effective to achieve high prediction performance.

### Comparison of encoding methods

To demonstrate the superiority of the nn.Embedding of FCS, five CA\_Ps with different encoding methods (Table 1) were tested on the DAVIS dataset, as shown in Fig 3 and S2 Table: nn.Embeddings of FCS, SMILES, SELFIES, and one-hot encodings of SMILES and SELFIES. nn.Embedding of FCS presented the highest SN, ROCAUC, and PRAUC values. nn.Embeddings of SMILES and SELFIES outperformed the one-hot encodings of SMILES and SELFIES, suggesting that nn.Embedding facilitates attention-based learning to a greater degree than one-hot encoding. This difference is due to the perceptron architecture implemented by nn.Embedding. nn.Embedding of SELFIES provided higher SP, ROCAUC, and PRAUC values than nn.Embedding of SMILES; one-hot encoding of SELFIES provided much higher SN, ROCAUC, and PRAUC values than one-hot encoding of SMILES. This result indicates that SELFIES is more effective than SMILES at learning features, because SELFIES decomposes chemical formulas into chemically meaningful character lists, whereas SMILES does not. These optimization processes confirmed that CA\_P with nn.Embedding of FCS is the optimal method, which was then designated ICAN.

### Comparison with state-of-the-art methods

We compared the optimal architecture of ICAN with 7 state-of-the-art methods on DAVIS, as shown in Fig 4 and S3 Table. S3 Table presents the values of all the six metrics including PR and F1. We employed a classical machine learning method, a linear regression (LR)-based model that used ECFP for encoding drugs and PSC for encoding proteins [40,54], and the following CNN-based models: GNN-CPI [34], DeepDTI [9], DeepDTA [30], DeepConv-DTI [33], and the latest attention mechanism-based methods of TransformerCPI [13] and MolTrans [40]. ICAN and MolTrans outperformed the CNN-based methods (GNN-CPI, DeepDTI, DeepDTA, and DeepConv-DTI) in terms of ROCAUC and PRAUC. In particular, ICAN provided the highest SN, ROCAUC, and PRAUC values for all of the methods, although MolTrans was very competitive compared with ICAN. ICAN and MolTrans exhibited higher SN, SP, ROCAUC, and PRAUC values than TransformerCPI. The high PRAUC value of the ICAN method suggests that it takes advantage in the imbalanced dataset. The CNN-based methods provided higher SN, ROCAUC, and PRAUC values than the classical machine learning model of LR. In the CNN-based methods, DeepDTA exhibited the highest SN, whereas DeepConv-DTI exhibited the highest ROCAUC and PRAUC values.

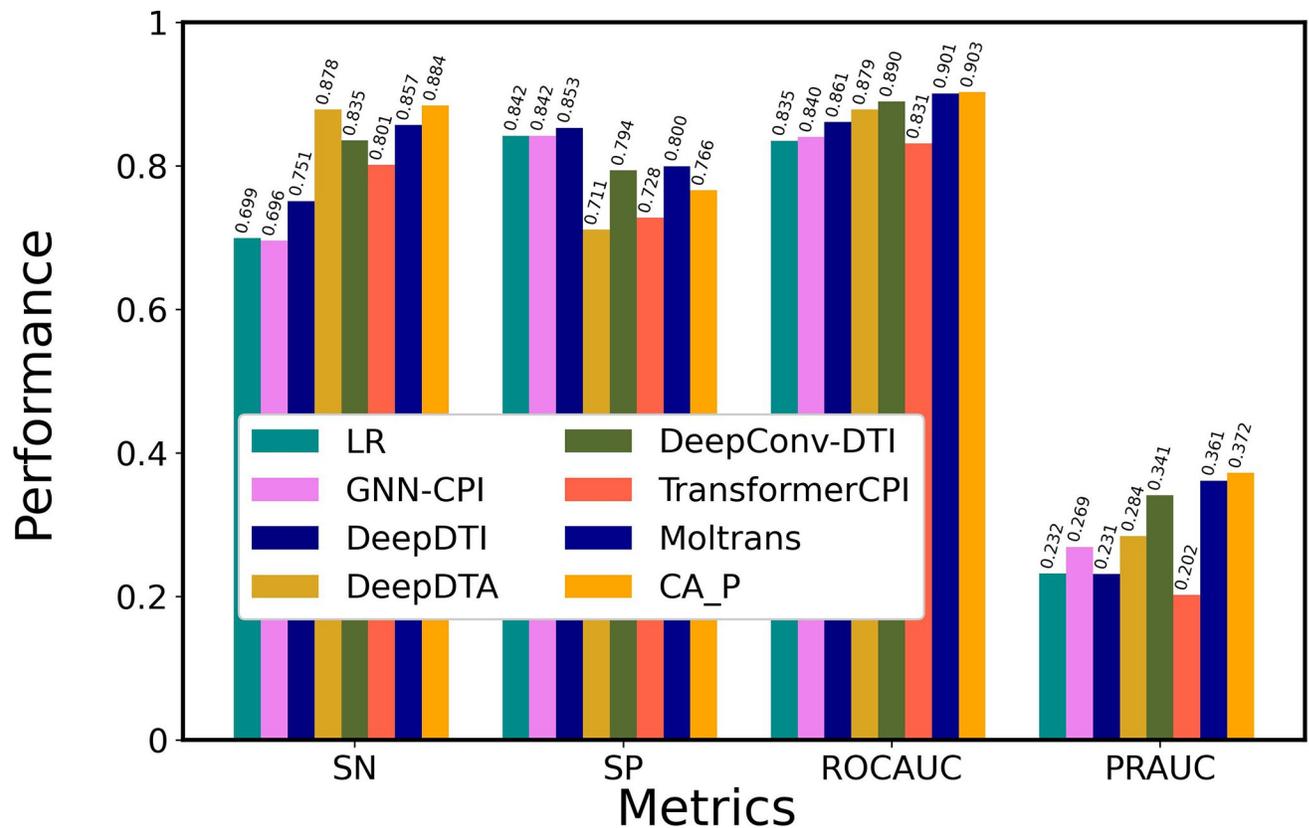


**Fig 3. Optimization of encoding methods.** CA\_Ps (ICANs) with 5 different encoding methods were trained using the DAVIS training dataset and evaluated using the DAVIS test dataset. Details regarding the encoding methods are shown in Table 1.

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### Robustness analysis

To characterize the robustness of the optimal network architecture of ICAN, we compared it with 7 state-of-the-art methods on the BindingDB and BIOSNAP datasets, as shown in Figs 5 and 6 and S4 and S5 Tables. In BindingDB (Fig 5, S4 Table), ICAN provided the highest

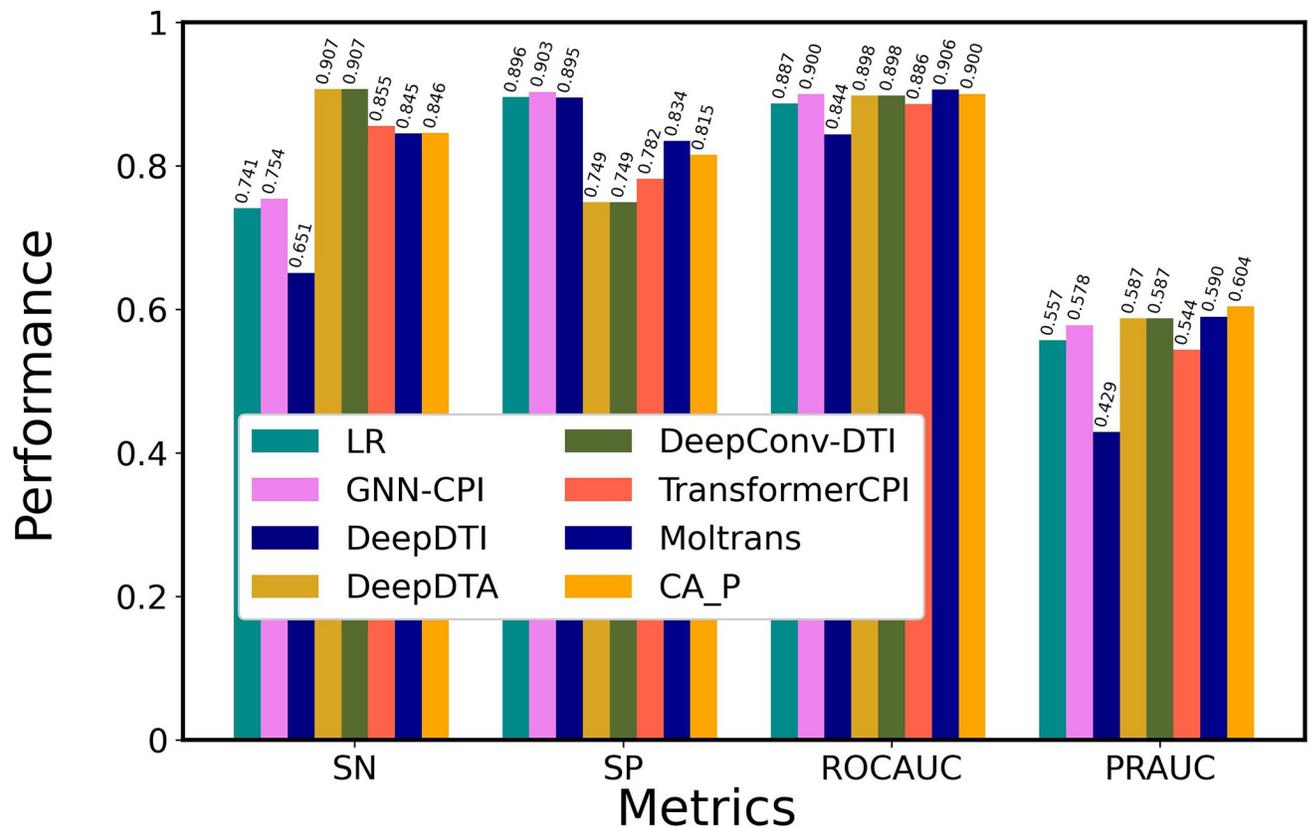


**Fig 4. Comparison of the performance of ICAN with that of state-of-the-art models on DAVIS datasets.** All models were trained using the DAVIS training dataset and evaluated using the DAVIS test dataset. CA\_P was designated ICAN.

<https://doi.org/10.1371/journal.pone.0276609.g004>

PRAUC value, whereas the CNN-based models (GNN-CPI, DeepDTA, and DeepConv-DTI) and MolTrans were competitive compared with ICAN in terms of ROCAUC and PRAUC values. For the three attention-based models (TransformerCPI, MolTrans, and ICAN), MolTrans and ICAN provided higher ROCAUC and PRAUC values than TransformerCPI. Although GNN-CPI provided high SP, ROCAUC, and PRAUC values, it exhibited poor performance on DAVIS. On BIOSNAP (Fig 6, S5 Table), the CNN-based methods (GNN-CPI, DeepDTI, DeepDTA, and DeepConv-DTI) provided high ROCAUC and PRAUC values that were competitive with or greater than those obtained with the three attention-based methods. DeepDTA provided the highest ROCAUC and PRAUC values for all of the methods. For the three attention-based models, MolTrans provided slightly higher ROCAUC and PRAUC values than ICAN, whereas TransformerCPI was competitive compared with ICAN. TransformerCPI functioned well using the balanced dataset (BIOSNAP), but it performed poorly on the imbalanced datasets (DAVIS, BindingDB).

The performance of the deep learning models including ICAN depended on the datasets. No method is ideal or perfect for all three datasets. ICAN provided the highest PRAUC value on the DAVIS and BindingDB test datasets (imbalanced dataset) but not on the BIOSNAP test dataset (balanced dataset). This suggests that ICAN has an advantage in predicting imbalanced test datasets. It is notable that the DAVIS and BindingDB test datasets contain a much greater abundance of negative samples than positive samples. In contrast, the BIOSNAP test dataset contains an equal number of negative and positive samples (Table 3). Both the attention-based



**Fig 5. Comparison of the performance of ICAN with that of state-of-the-art models on BindingDB.** All models were trained using the BindingDB training dataset and evaluated using the BindingDB test dataset. CA\_P was designated ICAN.

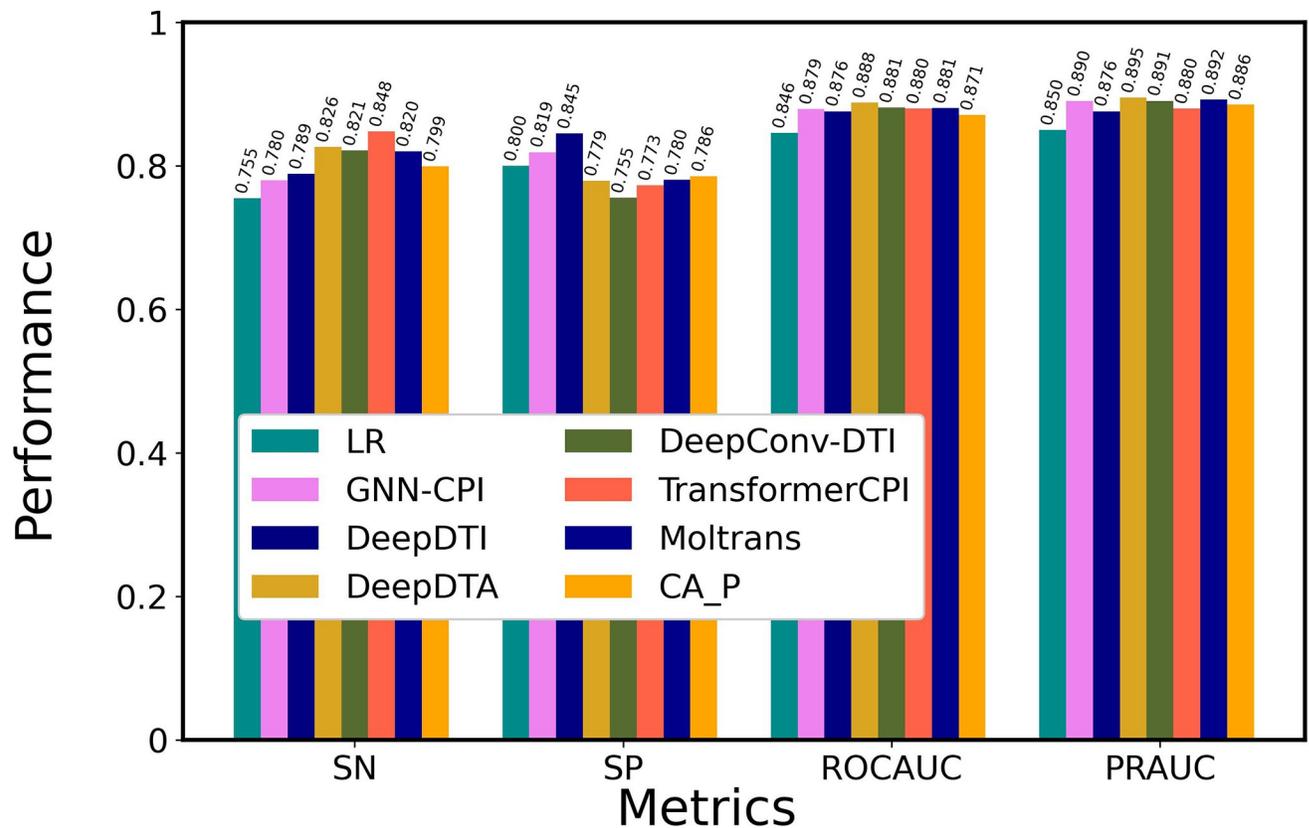
<https://doi.org/10.1371/journal.pone.0276609.g005>

methods (ICAN, MolTrans) and CNN-based methods (DeepDTA, DeepConv-DTI) exhibited competitive performance on the BindingDB test dataset. DeepDTA and DeepConv-DTI exhibited higher prediction performance on the BIOSNAP test dataset compared with the attention-based models. CNN may learn a large BIOSNAP dataset efficiently to provide high performance.

It is essential that DTI predictors exhibit generalization capability and robustness for external tests and practical applications. To this end, we must understand what deep learning models learn that can affect the generalization capability and use not only publicly available data for drugs and proteins but also unlabeled biochemical and biophysical data, including structural information. In this regard, structural information emerging from the AlphaFold Protein Structure Database [55] would be useful for enabling accurate predictions.

### Interpretability of binding mechanism

To demonstrate the interpretability of the attention mechanisms, we fed the 160 DTIs with their binding sites into ICAN to generate corresponding attention weight matrixes (Fig 7A) and calculated the experimental consistency number between the top 30 attention sites and the experimental drug-binding sites as 2.020 (Fig 7B). We found that approximately 2 of the 30 attention sites corresponded to the experimental binding sites for each target protein. To statistically evaluate this number, we generated 10,000 simulated consistency numbers between

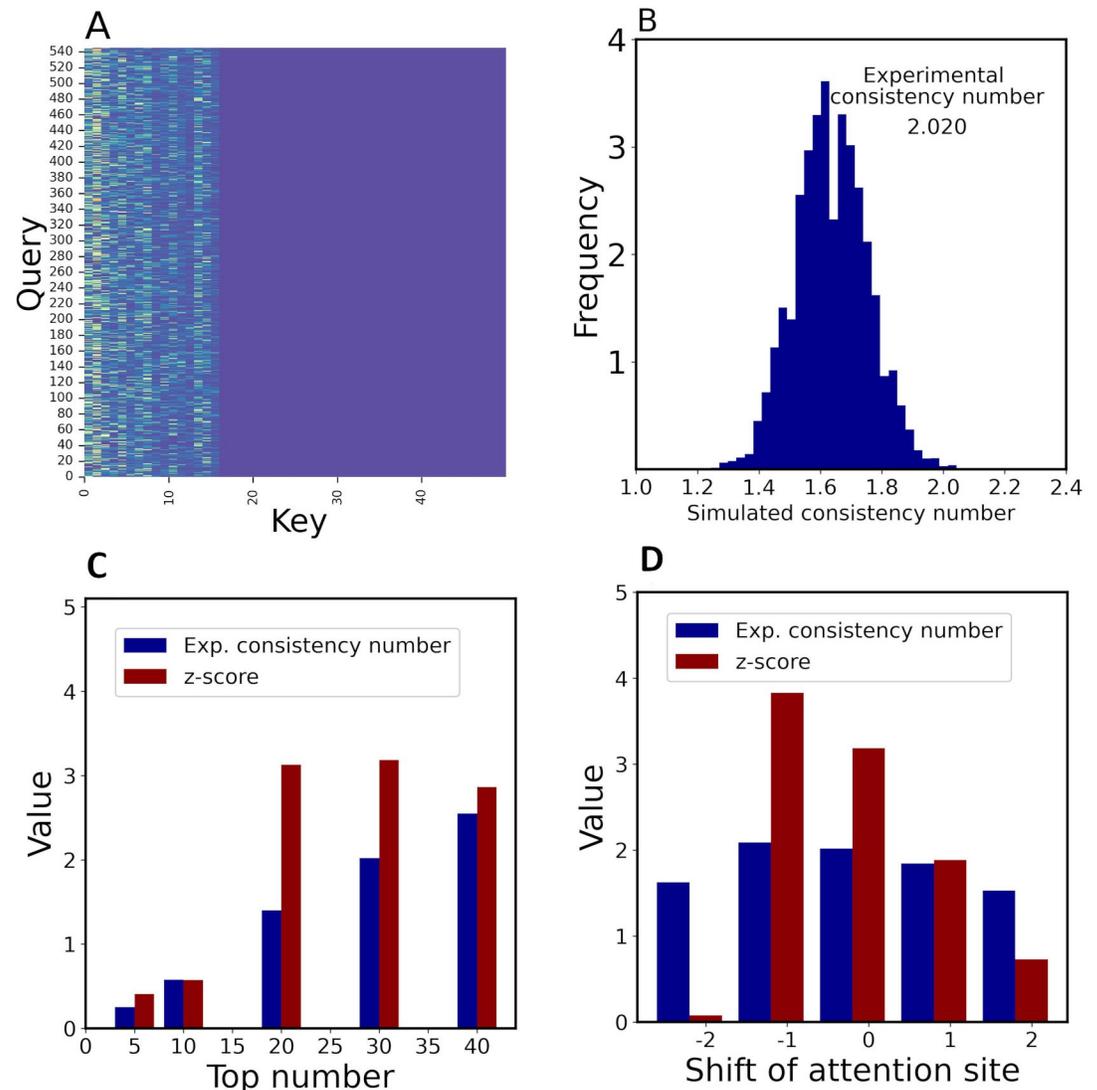


**Fig 6. Comparison of the performance of ICAN with that of state-of-the-art models on BIOSNAP.** All models were trained using the BIOSNAP training dataset and evaluated using the BIOSNAP test dataset. CA\_P was designated ICAN.

<https://doi.org/10.1371/journal.pone.0276609.g006>

the top 30 attention sites and randomly generated binding sites of proteins for 160 DTIs (Fig 7B). The mean and standard deviation of the consistency number were 1.64 and 0.119, respectively. Based on this profile, the calculated z-score for the experimental consistency number (2.020) was 3.186, indicating that the attention sites were definitely related to the experimental binding sites.

To determine why it is necessary to use the top 30 attention sites, we investigated how a change in the maximum number of attention sites affects the experimental consistency numbers and their corresponding z-scores, as shown in Fig 7C. Using the top 30 attention sites provided the greatest increase in both the experimental consistency number and z-score. Thus, we selected the top 30 attention sites. Another reason was that the average number of experimental binding sites was approximately 28.9 (~30) for each target protein. Using the top 10 attention sites provided a small experimental consistency number of 0.5, whereas the top 30 attention sites provided a number of 2. This suggests that the top-ranked attention site does not always represent the binding site. Only 2 of 30 attention sites corresponded to binding sites, whereas the remaining 28 did not. The remaining sites may interact indirectly with the binding sites or affect the biochemical and/or structural properties of DTIs. Consequently, although the binding sites are clearly focused by the attention mechanism, they are not priority factors of the mechanism. It would be very interesting to identify what the attention mechanism actually focuses on.



**Fig 7. Attention-weight analysis.** 160 DTIs with their binding sites were tested by ICAN. The simulation was iterated 10,000 times. (A) Attention-weight matrix for the DTI between DB06896 and P08581 (hepatocyte growth factor receptor). (B) Profile of simulated consistency numbers between the top 30 attention sites and randomly generated binding sites. (C) Effect of the number of top attention sites on experimental consistency numbers and associated z-scores. Experimental consistency numbers and associated z-scores were calculated with respect to a change in the top attention site number. (D) Effect of a shift of attention sites on experimental consistency number and their z-score values.

<https://doi.org/10.1371/journal.pone.0276609.g007>

To further validate the relationship between attention sites and experimental binding sites, we shifted the attention sites by  $-2$ ,  $-1$ ,  $0$ ,  $1$ , and  $2$  to calculate the experimental consistency numbers and corresponding z-scores. Zero indicates no shift of the attention sites, whereas a value of  $1$  indicates that the attention site was up-shifted by one amino acid. As shown in Fig 7D, a shift of  $-1$  did not reduce the experimental consistency number and its corresponding z-score, whereas shifts of  $-2$ ,  $1$ , and  $2$  decreased these values. These results demonstrate that the attention mechanism focuses on the exact binding site and neighboring sites.

Recently developed attention-based deep learning models have suggested that attention can be interpreted by investigating the relationship between highly weighted attention sites and

experimental binding sites. Data from TransformerCPI suggested that weighted attention sites are related to binding sites of transforming growth factor-beta type 1 receptor and C-X-C chemokine receptor type 4 [13]. MolTrans suggested binding sites for Ephrin type-A receptor and Dasatinib and binding sites for histone deacetylase 2 and hydroxamic acid [40]. Although these studies provided a few successful examples, they did not conduct statistical analyses of the results. To overcome this limitation, we first conducted a statistical analysis to determine the relationships between the attention sites and experimental binding sites and discovered that the attention sites were closely related to the experimental binding sites. This conclusion resulted from the plain structure of the cross-attention mechanism, which directly reads the drug and protein encoding features (Fig 1).

## Conclusions

We designed an attention-based DTI method designated ICAN, which is composed of an embedding layer, attention mechanism, and output layer. Analyses of the attention mechanism factors (cross attention/self-attention, attention layer depth, selection of context matrixes from the attention networks, and output layer algorithms [CNN or fully connected layer]) revealed that the plain cross-attention mechanism with CNN and CA\_P (ICAN) provided the highest prediction performance. The cross-attention mechanism considers sub-sequence interactions between a drug and a protein to produce context matrixes; the subsequent CNN extracts local sub-sequence patterns within the context matrixes using different filters. ICAN successfully decodes drug-related protein context features without the need for any protein-related drug context features. This is similar to TransformerCPI, which decodes protein features based on encoded drug features, but it is not consistent with MolTrans, which uses two self-attention mechanisms. MolTrans implements an interaction map that integrates the drug and protein context features from the self-attention mechanism to complement the lack of a cross-attention mechanism between drugs and proteins. We then selected nn.Embedding of FCS as the best of the five encoding methods: nn.Embedding of FCS, nn.Embedding of SMILES, nn.Embedding of SELFIES, one-hot encoding of SMILES, and one-hot encoding of SELFIES. Furthermore, we found that SELFIES was more effective than SMILES in terms of DTI prediction, because SELFIES decomposes chemical formulas into a chemically meaningful character list, but SMILES does not.

We also characterized the optimal architecture of ICAN in comparison with 7 state-of-the-art methods: a classical LR-based method, CNN-based models (GNN-CPI, DeepDTI, DeepDTA, and DeepConv-DTI), and the latest attention mechanism-based methods (TransformerCPI, MolTrans). ICAN provided the highest PRAUC value on the imbalanced datasets (DAVIS, BindingDB) but not on the balanced dataset (BIOSNAP). These results suggest that ICAN has an advantage in predicting imbalanced test datasets. The attention-based methods provided higher ROCAUC and PRAUC values than CNN-based models on DAVIS. Both the attention-based methods (ICAN and MolTrans) and CNN-based methods (DeepDTA and DeepConv-DTI) showed very competitive performance on BindingDB. DeepDTA and DeepConv-DTI exhibited better performance than the attention-based models on BIOSNAP. No best method was identified for all three datasets. These results indicate that the performance of deep learning models depends on the dataset.

The important task is to first conduct a statistical analysis to clearly determine the relationships between attention sites and experimental binding sites. ICAN was shown to enable the interpretation of various DTI mechanisms. We consider that such interpretability results from the plain structure of the cross-attention mechanism between a drug and protein. On the other hand, our analyses also suggested that the attention mechanism captures critical factors other

than binding sites, as it was shown to explain only a few of the 30 attention sites considered. To further increase the interpretability and robustness in examining independent datasets, it is necessary to determine exactly what the attention mechanism really captures and how this affects the generalization capability. Additional DTI predictors remain to be developed using different chemo-genomics approaches.

## Supporting information

### S1 Fig. Self-attention-based model.

(PDF)

### S2 Fig. Cross-attention-based model.

(PDF)

### S1 Table. Performance of different network architectures.

(PDF)

### S2 Table. Performance of different encoding methods in CA\_P (ICAN).

(PDF)

### S3 Table. Performance of different learning methods on the DAVIS test dataset.

(PDF)

### S4 Table. Performance of different learning methods on the BindingDB test dataset.

(PDF)

### S5 Table. Performance of different learning methods on the BIOSNAP test dataset.

(PDF)

## Acknowledgments

We are grateful to Mitsuki Watanabe for collecting DTI binding-site data.

## Author Contributions

**Methodology:** Sho Tsukiyama.

**Writing – original draft:** Hiroyuki Kurata.

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