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Predicting Comprehensive Drug - Drug Interaction via Similarity Network Fusion and Convolutional Neural Networks

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Abstract

Background: Drug-drug interactions (DDIs) usually cause unexpected and even adverse drug reactions. It is important to identify DDIs before using them in the market. However, preclinical identification of DDIs requires much money and time. Computational approaches have exhibited their abilities to predict potential DDIs on a large scale by utilizing premarket drug properties. Nevertheless, most of them only predict whether or not one drug interacts with another, but neglect their enhancive (positive) and depressive (negative) changes of pharmacological effects. Moreover, these comprehensive DDIs do not occur at random, and derived from the structural features of the graph of DDIs. Revealing such a relationship is very important, because it is able to help understand how DDIs occur. Prediction of comprehensive DDIs and the discovery of structural relationships in the DDI graph play important guidance when making a prescription of multiple drugs.

Results: In this work, treating a set of comprehensive DDIs as a signed network, we design a novel model (SNF-CNN) for the prediction of enhancive or depressive of a pair of drugs based on similarity network fusion and convolutional neural networks. SNF-CNN achieves the depressive DDI prediction ($AUC = 0.975$ and $AUPR = 0.967$), enhancive DDI prediction ($AUC = 0.969$ and $AUPR = 0.822$) and the Unknown DDI prediction ($AUC = 0.971$ and $AUPR = 0.948$). Compared with three state-of-the-art methods on a dataset, SNF-CNN shows superiority.

Conclusions: This new approach is not only able to predict comprehensive DDI, but also predicts non-DDI accurately.

Keywords: Drug-Drug Interaction; Drug Similarity; Drug Similarity Integration; Feature Selection; Recommender System

Introduction

When two or more drugs are taken together, drugs' effects or behaviors are unexpectedly influenced by each other [1]. This kind of influence is termed as Drug-Drug interaction (DDI), which would reduce drug efficacy, increase unexpected toxicity, or induce other adverse drug reactions between the co-prescribed drugs. As the number of approved drugs increases, the number of drug-unidentified DDIs is rapidly increasing, such that among approved small molecular drugs in Drug Bank, on average, 15 out of every 100 drug pairs have known DDIs [2]. The DDIs would put patients, who are treated with multiple drugs, in an unsafe situation [3, 4, 5, 6]. Understanding DDI is the first step in drug combinations, which becomes one of the most promising solutions for the treatment of multifactorial complex diseases [7].

Therefore, there is an urgent need for screening and analysis of DDIs before clinical co-medications are administered. However, traditional DDI identification approaches (e.g., testing Cytochrome P450 [8] or transporter-associated interactions [9]) face challenges, such as high costs, long duration, animal welfare considerations [10], the very limited number of participants in the trial, and the great number of drug combinations under screening in clinical trials. As a result, only a few DDIs have been identified during drug development production (usually in the clinical trial phase). Some of them have been reported after drugs approved, and many have been found in post-marketing surveillance.

Computational approaches are a promising alternative to discovering potential DDIs on a large scale, and they have gained attention from academy and industry recently [11, 12]. Data mining-based computational approaches have been developed to detect DDIs from various sources [10], such as scientific literature [13, 14], electronic medical records [15], and the Adverse Event Reporting System of FDA (<http://www.fda.gov>). These approaches rely on post-market clinical evidence. So, they cannot provide alerts of potential DDIs before clinical medications are administered. In contrast, machine learning-based computational approaches (e.g. Naïve Similarity-Based Approach [16], Network Recommendation-Based [10], Classification-Based [17]) can provide such alerts by utilizing pre-marketed or post-marketed drug attributes, such as drug features or similarities [18]. These methods use different drug features to predict DDIs, such as chemical structures [16], targets [19], hierarchical classification codes [17], side effects, and off-label side effects [10, 20].

A Dependency-based Convolutional Neural Network (DCNN) has proposed for drug-drug interaction extraction by Liu and et al. in 2016 [21]. DCNN is a text-mining approach which predicts DDIs based on unstructured biomedical literature and the existing knowledge bases. It applies convolution layers on word sequences as well as dependency parsing trees of candidate DDIs for adjacent words. DeepDDI has proposed by [22], which is a combination of the structural similarity profile generation pipeline and Deep Neural Network (DNN). DeepDDI predicts DDIs from chemical structures and names of drug-drug or drug-food constituent pairs. It has various implications for adverse drug events such as prediction of potential causal mechanism and using them for output sentences.

Although previous methods had great advances, more prediction accuracy is still needed. Exploiting more similarities may help to make more advances in this problem. Similarity Network Fusion (SNF) [23] is a competent method to integrate various similarities, which is used in numerous biological contexts [24, 25, 26]. The neural network is a strongly developed approach that provides satisfactory solutions, especially for large datasets and nonlinear analyzes [27], which is widely used in critical problems [28, 29, 30].

Most of these existing machine learning approaches are designed to predict the typical two-class problem, which only indicates how likely a pair of drugs is a DDI. However, two interacting drugs may change their own pharmacological behaviors or effects (e.g., increasing or decreasing serum concentration) *in vivo*. For example, the serum concentration of Flunisolide (DrugBank Id: DB00180) decreases when it is taken with Mitotane (DrugBank Id: DB00648), whereas its serum concentration

increases when taken with Roxithromycin (DrugBank Id: DB00778). For short, the first case is degressive DDI, and the second case is enhancive DDI, which contains drug changes in terms of pharmacological effects. It is more important to know exactly whether the interaction increases or decreases the drug's pharmaceutical behaviors, especially when making optimal patient care, establishing drug dosage, designing prophylactic drug therapy, or finding the resistance to therapy with a drug [31].

Besides the occurrence of both enhancive and degressive DDIs is not random [32, 33], however most current approaches have not yet exploited this structural property and have been developed only for conventional two-classes DDIs. Furthermore, revealing such a structural relationship is very important because it can help to understand how the DDIs occur. It is one of the most important steps for treating complex diseases [34] and guides physicians in preparing safer prescriptions to high-order drug interaction.

The recent works attempted to investigate two major issues: 1) predicting three-class DDIs instead of two-class prediction, 2) extracting the topological information of drugs in a DDI network.

Model of TMFUF [32] is proposed by Shi and et al. in 2018 which predicts enhancive and degressive DDIs for different predicting scenarios of new drugs (those with no known DDI). Proposed DDINMF model [33] in addition to predicting DDIs, assigns every drugs to drug communities. In result, some correlations are observed between drug communities and the numbers of enhancive, degressive, sum and difference of DDIs for each drug.

These observation shows that not only occurrence of enhancive or degressive DDIs are not randomly but also represents some topological features in DDI network. BRSNMF [35] model is a method based on Semi-NMF to predict the degressive and enhancive DDIs, more accurately, in cold start scenario [36]. This method exploits Drug Binding Protein (DBP) feature to map new drugs (without any known DDIs) with known drugs (drugs which has one DDI at least). Results show that BRSNMF defines drug communities with more moderate sizes by adding a regularization term to Semi-NMF objective function based on weakly balance theorem.

All three introduced algorithms are using matrix factorization methods, which are a network recommender-based approach. The matrix factorization approach, with slight modification, is a suitable solution for the subject of predicting DDI that has received much attention from researchers, but these methods do not work on potential DDIs which are crucially important in giving safer prescriptions.

In this paper, we firstly introduce data and features. Then, a novel algorithm based on the integration of drug similarities and deep learning recommendation systems for predicting DDI is presented in a comprehensive three-class model. This algorithm is called Predicting Comprehensive Drug-Drug Interaction via Similarity Network Fusion and Convolutional Neural Networks (SNF-CNN). The SNF-CNN trying to recognize unknown and potential DDIs which are not detected yet. The feature's intrinsic of off-label side effect and chemical structure of drugs may provide information to find hidden potential DDIs in current DDI network. To use both of similarity features, we will take advantage of SNF.

The paper is organized as follows. In the first section, the data preparation process is explained. The recommendation system is then designed and trained on enhancive

and degressive, which detects pairs of non-interacting drugs with high probability. Next, the previous recommender system, based on a convolutional neural network, is trained on incremental and decremental interaction data without interaction (detected in the previous step). In section Results and Discussions, we investigate the DDI prediction results of SNF-CNN in the 10-fold cross-validation (CV) process in compare to other methods.

It should be noted that the proposed method of this research is a recommender-based on deep neural networks and has no structural similarities with matrix factorization methods. The only reason for mentioning these methods is the limited number of articles that have used three-class data in their work.

Methods

Dataset and features

In this study, we use the data set presented by Yu and et al. in 2018 [33]. This set contains 568 approved small molecule drugs, each of them has at least one interaction with the other drugs in the set. In total, the interactions between these 568 drugs contain 21,351 DDIs, including 16,757 enhance DDIs and 4,594 degressive DDIs. In addition, each drug represented as an 881-dimensional feature vector F_{str} based on PubChem chemical structure descriptor and also a 9149-dimensional feature vector F_{se} based on the off-label side effects provided by OFFSIDES. If a side effect or chemical structure is reported or has observed for the drug its vector element is one, otherwise is zero.

Problem formulation

Without loss of generality, let $D = \{d_i\}$, $i = 1, 2, \dots, m$ be a set of m approved drugs. In addition, each drug d_i in the D is represented as a p -dimension feature vector $f_i = [f_1, f_2, \dots, f_k, \dots, f_p]$, which $f_k = 1$ indicates the K -th specific chemical structure fragment or occurs an off-label side effect, and $f_k = 0$ otherwise. Because each drug has two feature vectors of the chemical structure and the off-label side effect. There are two feature matrices of F with dimensions of $m \times p$ (magnitude of p depends on kind of feature). Matrices of F_{str} and F_{se} are, respectively, the feature matrix of the chemical structure and the feature matrix of off-label side effects.

Drug-Drug interactions can be accordingly represented as an $m \times m$ symmetric interaction matrix $A_{m \times m} = \{a_{ij}\}$. For the conventional binary DDIs, $a_{ij} = 1$ if d_i interacts with d_j , and $a_{ij} = 0$ otherwise. Matrix of comprehensive DDIs has three amounts ($a_{ij} \in \{-1, 0, +1\}$). Same as binary formulation, if d_i and d_j do not interact with each other, $a_{ij} = 0$ while there is an enhance DDI or a degressive DDI between d_i and d_j , $a_{ij} = +1$ or $a_{ij} = -1$ respectively.

Data preparing

Since, the new drugs are isolated nodes in the interaction network, we cannot infer their possible interaction from topological information alone. Therefore, additional information (such as chemical structure or off-label side effects) is needed, which is called a drug feature in terms of machine learning. First, we prepare feature matrix data to be proper input for machine learning methods then we devise and train a deep learning model to predict potential interactions.

Similarity matrix calculation

A common method of calculating similarity called Cosine Similarity is used in machine learning articles such as Articles [37, 38]. If we name feature vectors of the drug of d_i and d_j as x_i and x_j , Cosine Similarity between x_i and x_j is defined as follows:

$$S_{Cos}(x_i, x_j) = \frac{x_i \cdot x_j}{\|x_i\|_2 \|x_j\|_2} \quad (1)$$

Where $\|\cdot\|_2$ is the Euclidean Norm and $x_i \cdot x_j$ is inner product of two vectors.

It was observed that the values of the feature matrices are discrete, and also the dimensions of the matrices are large. The chemical structure and the off-label side effect have 881 and 9149 dimensions, respectively. On the other hand, machine learning algorithms do not work properly with high-dimensional data and discrete data. As a result, they do not get good results on these kinds of data. Therefore, by exploiting the cosine similarity, that was described above, drug similarity matrices based on chemical structure and off-label side effects are calculated. These matrices are S_{str} and S_{se} , respectively. The dimensions of these two matrices are $m \times m$, where $s_{i,j}$ is an element of similarity matrices that shows similarity value between drugs of d_i and d_j . Each element of S has a continuous value between zero and one.

Integration drug similarity matrices

Similarity Network Fusion (SNF)[23] is a new computational method for data integration. Briefly, SNF combines many different types of features (such as chemical structure and off-label side effect, and more - clinical data, questionnaires, image data, etc.) for a given set of samples (e.g., drugs). SNF first constructs a sample similarity network for each of the data types and then iteratively integrates these networks using a novel network fusion method. Working in the sample network space allows SNF to avoid dealing with different scales, collection bias, and noise in different data types. Integrating data in a non-linear fashion allows SNF to take advantage of the common and complementary information in different data types. Figure 1 is a good visualization of SNF processes that has been used in our method structure.

In this section, using the similarity network fusion method that has described above, similarity matrices of the chemical structure and the off-label side effect of drugs were integrated. The output of this integration is a new similarity matrix of S_{snf} with dimensions of 568×568 , and elements of S_{snf} have a value between zero and one. To integrate the network similarity, the package of SNFPy is used, which is implemented in Python and is available at [39].

Input matrix format

At this stage, a matrix forms with 1139 columns and 322056 rows, which consists of the following columns:

- 1) Drug pairs: Name of the drug i-th and the name of the drug j-th.
- 2) Type of interaction: degressive (-1), enhancive (+1), and unknown (0).
- 3) The similarity vector of i-th drug from the S_{snf} matrix with 568 elements.
- 4) The similarity vector of j-th drug from the S_{snf} matrix with 568 elements.

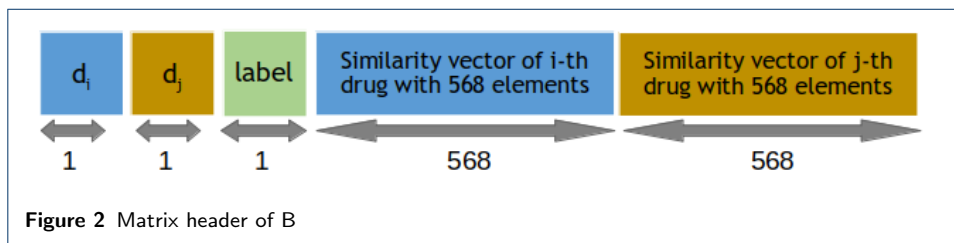
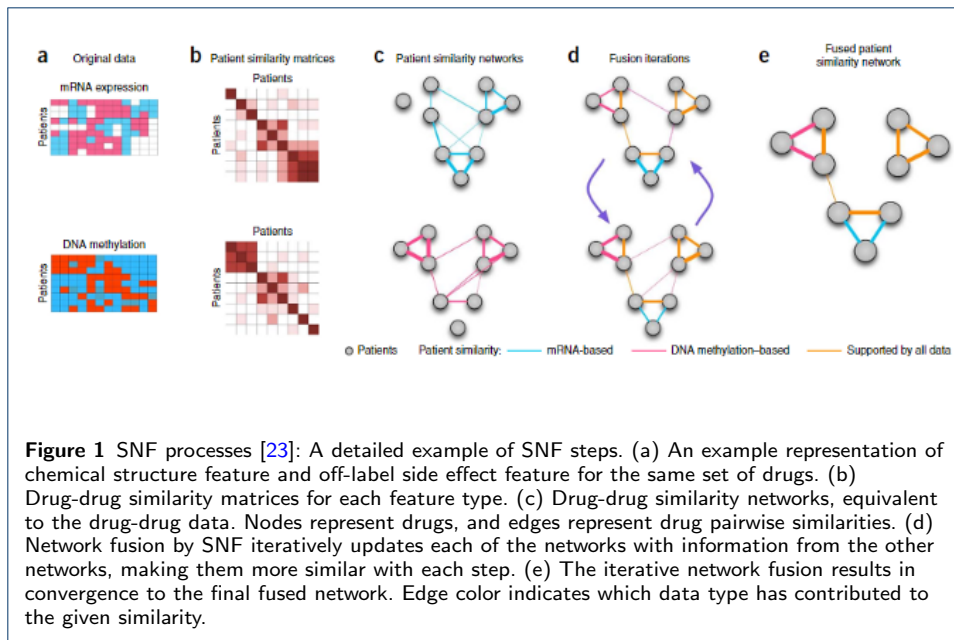


Figure of 2 shows the header of matrix.

We have 568 drugs, and the interaction of each drug with itself is meaningless. On the other hand, the drug pairs of (d_i, d_j) and (d_j, d_i) have the same label, while the corresponding similarity vectors of drugs in the drug pairs have been displaced. So, these drug pairs are dual. Both of them in the data augment the training data, which increases the model's ability to have a better prediction. As a result, the resulting matrix has 322056 data samples or rows $((568 \times 568) - 568 = 322056)$. According to the explanations provided, a matrix with dimensions of 322056×1139 is formed to input into our model, which is called B .

Devising of Recommender System

In the previous steps, data was prepared to input any learning machine, including deep learning machines. But before presenting the model and inputting the data into the machine, one important point must be considered. As mentioned before, in this approach and other approaches, the positive and negative data have a specific label. While the zero label does not mean that there is no interaction between a pair of drugs, it does indicate that no interaction has yet been found for this pair of drugs. In the following, we present a method for detecting pairs of non-interacting drugs. Then we use these pairs of drugs as zero-labeled data in the next training.

Assessment

K-Fold cross-validation (CV) is a well-proven approach to verify the algorithms' resolution ability, model selection, and feature engineering in machine learning. To demonstrate that the feature set is informative enough, the selected model is robust and confident or the method has proper accuracy in comparison with other methods, the CV equation must be carefully designed. The production of test and experimental samples is as follows:

The whole data set has divided into K equal parts with consideration of dual pairs. Since biologically, the (d_i, d_j) and (d_j, d_i) drug pairs are the same we expect the model to predict their labels similarly. In the separation of training and testing data, necessarily a drug pair and its dual are in the same group to prevent unfair results. The K-1 parts are used as a training data set, and the model has built based on them, and the test has performed with a remaining part. This procedure has repeated K times so that each of the K parts has used only once for testing, and each time a resolution metric has calculated for the constructed model. In this method, the average prediction resolution metric in all K rounds is taken as the final resolution metric for the classifier. The most common value for K in scientific literary is 5 or 10. Obviously, the more detailed validation in the K-fold CV the more reliable the classifier accuracy, the more comprehensive the obtained knowledge, and the more time-consuming the validation process.

Evaluation Criteria for Model Selection step

In this study, we classify drug pairs into three classes, according to the type of interaction or non-interaction, so in order to compare the method performance with other existing methods, six measurement criteria of Precision, Recall, F- measure, accuracy, Area Under Roc Curve (AUC), and Area Under Precision-Recall Curve (AUPR) are used. In order to define these criteria, at first, introduced four counting criteria in Table 1.

	Actual Enhance	Actual Degressive
Classified Enhance	<i>TP</i>	<i>FP</i>
Classified Degressive	<i>FN</i>	<i>TN</i>

Table 1 The confusion matrix for interaction type (Degressive or Enhance) and relevant evaluation index. True Positive (TP): The number of drug pairs classified as enhance interaction correctly, False Positive (FP): The number of drug pairs classified as enhance interaction incorrectly, False Negative (FN): The number of drug pairs classified as degressive interaction incorrectly, True Negative (TN): The number of drug pairs classified as degressive interaction correctly.

If consider degressive interaction as Negative (N) and enhance interaction as Positive (P) sample then the confusion matrix for interaction type (Degressive or Enhance) and relevant evaluation index is as shown in Table 1. By using Table 1, four evaluation criteria are defined in the following order:

Accuracy: The fraction of all correct predictions (TP and TN) to all predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision: The fraction of correct predicted (enh/deg) interactions among all predicted (enh/deg) interactions.

$$\text{Precision}_{(enh/deg)} = \frac{TP}{TP + FP}$$

Recall: The fraction of correct predicted (enh/deg) interactions among all true (enh/deg) interactions.

$$\text{Recall}_{(enh/deg)} = \frac{TP}{TP + FN}$$

Precision and recall have a trade-off; thus, improving one of them may lead to a reduction in another. Therefore, utilizing F-measure is more reasonable.

F-measure: The geometric mean of precision and recall.

$$F - measure_{(enh/deg)} = \frac{2 \times \text{Precision}_{(enh/deg)} \times \text{Recall}_{(enh/deg)}}{\text{Precision}_{(enh/deg)} + \text{Recall}_{(enh/deg)}}$$

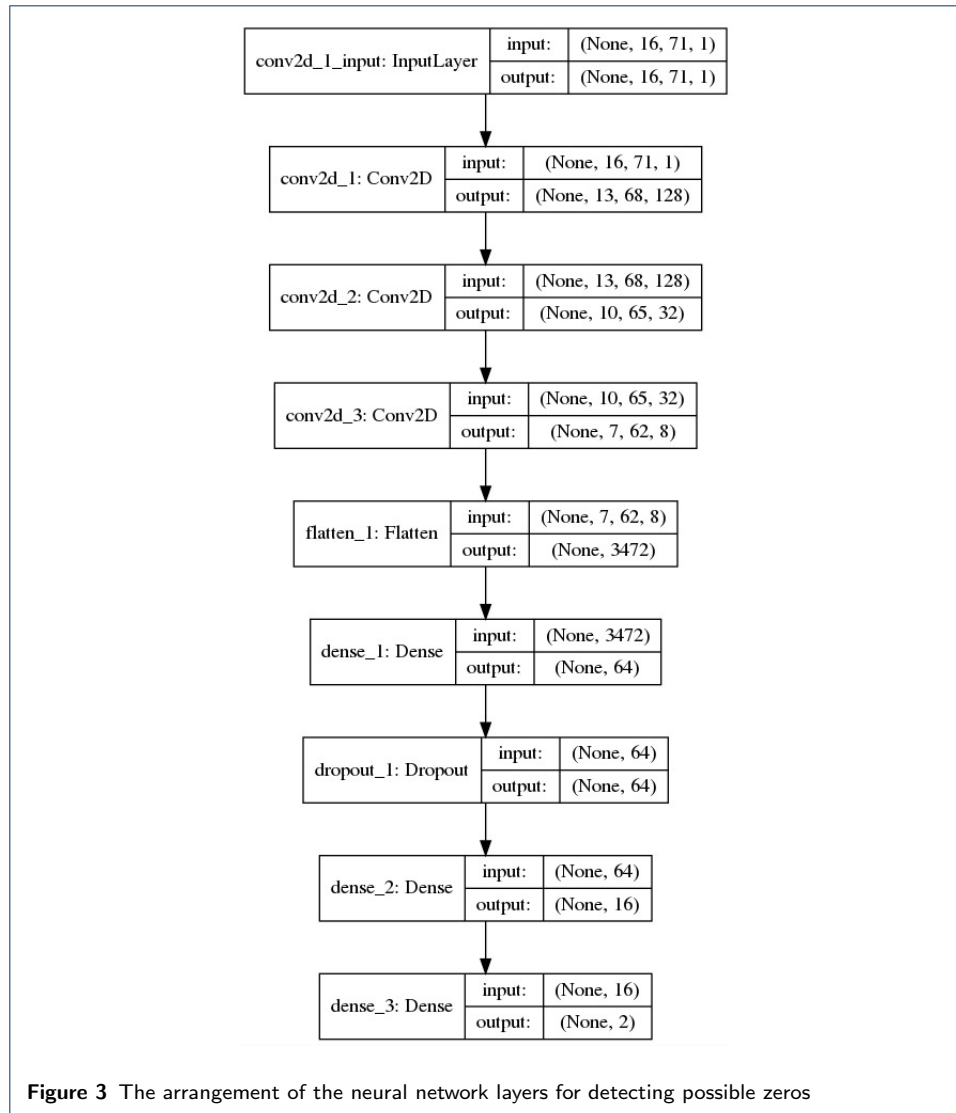
Since the values of precision, recall, and F-measure is dependent on the value of the threshold, we also evaluate methods via AUC which is the area under the receiver operating characteristic (ROC) curve, and AUPR, that is the area under the precision-recall curve. These criteria indicate the efficiency of methods independent of the threshold value. In cases that the fraction of negative samples and positive samples are not equal, AUPR is the fairer criterion for evaluation.

Selecting and training model on known interactions

To solve this problem, it is necessary to provide a model that detects non-interaction with high resolution and confidence. Therefore, we design a model based on deep learning that predicts the possible non-interaction drug pairs and then use it to design a three-class model. Obviously, high resolution in detecting these zeros can help provide a more accurate and confident three-class model.

Selecting model

We separated rows of matrix B that contain positive and negative interactions. The new matrix contains 42,702 pairs of drugs with degressive and enhancive interactions. This data was used to train and find a more suitable model and found a stronger model among many models with different network structures. The final model was a deep neural network that used convolutional and fully connected layers. The features of all interactions (+1 and -1) contain 1136 features. We first divide these features into 10 equal parts. Then, in a 10-cycle for, each period we consider 1 part as testing data and the other 9 parts as a set of training data. We select different models and train the model in the 10-fold CV with 90 of the data. Then we test the model on the remaining 10 percent of the data. In the separating process, pairs of drugs dual are considered. Since the (d_i, d_j) and (d_j, d_i) pairs of drugs are not biologically different from each other, in the separation of training and testing data, necessarily a pair of drugs and their dual are in the same group. This prevents unfair results.



After testing the different structures, we have modeled the final deep neural network shown in Figure 3.

This network has three layers of two-dimensional convolution. In the following, there are three fully connected convolution layers. The last layer has two outputs for predicting degressive or enhancive interaction. Convolution layers have 4-dimensions square filters with a Stride of 1. Each convolution layer also has a Rectified Linear Units (ReLU) activation function [40], which is defined as the positive part of its argument:

$$ReLU(x) = \max\{x, 0\} \quad (2)$$

The number of convolution filters is 128, 32, and 8, respectively. All connected layers have 64, 16, and 2 nodes, respectively. The first two layers have the activation

function of ReLU, and the last layer with 2 nodes has a Sigmoid activation function [41], which is calculated as follows:

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (3)$$

Convolution layers using a Flatten layer Connects to fully connected layers. The function of this layer is to transform a two-dimensional matrix into a one-dimensional vector. The output of this input layer of the first layer is fully connected. Also, between fully connected 64 and 16 nodes, we used one Dropout layer [42] with a wast value of 0.2. This value indicates that the network in this layer does not randomly consider 20 percent of the features. This layer is used to prevent over-fitting of the model and forces the model to extract and use more features with more confidence for prediction. If some of them are removed, the algorithm's prediction power either doesn't decrease or doesn't rely on a few specific features.

Our studies and trials have shown that two-dimensional convolution layers work better than their one-dimensional counterparts because in this case, the filters can detect more drug similarities, and it is possible to extract more powerful Features. Therefore, the 1136-dimension feature vectors are transformed into matrices with dimensions of 71 16 times. Figure 4 shows the number of learnable weights for each layer. Also, the total number of weights is calculated, which indicates the general complexity of the model.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 13, 68, 128)	2176
conv2d_2 (Conv2D)	(None, 10, 65, 32)	65568
conv2d_3 (Conv2D)	(None, 7, 62, 8)	4104
flatten_1 (Flatten)	(None, 3472)	0
dense_1 (Dense)	(None, 64)	222272
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 16)	1040
dense_3 (Dense)	(None, 2)	34
Total params: 295,194		
Trainable params: 295,194		
Non-trainable params: 0		

Figure 4 Learnable parameters of two-class Neural Networks

The following settings are used in the construction of the convolution neural network:

- 1) We used Tensorflow [43] (version 1.14.0) and KERAS [44] (version 2.2.5) packages to implement the neural network.
- 2) The categorical-cross entropy loss function was considered an objective function for the neural network, which is generally used to train a classification network [45, 46, 47].

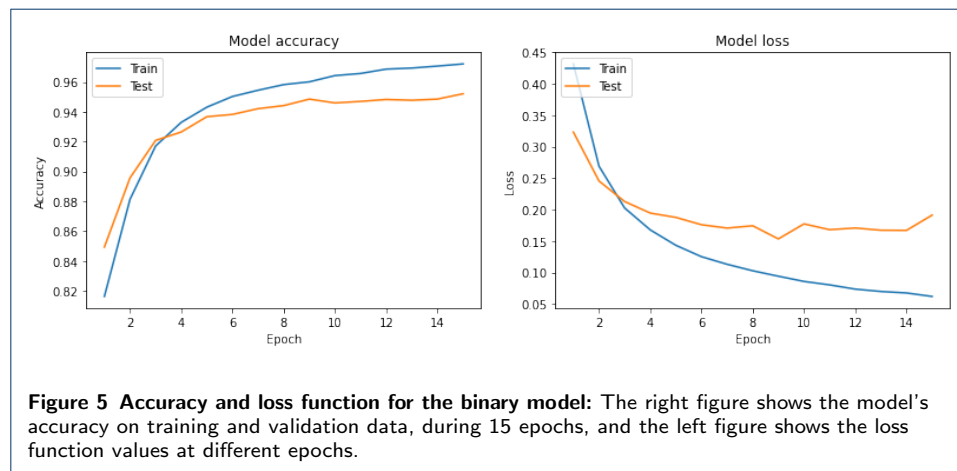
3) ADAM optimization [48] was used to manipulate the neural network weights to find a promising optimal (minimum) state of the loss function.

4) The number of epochs was considered 5.

5) Learning rate of 1.0×10^{-5} was used.

Two-class model's training trend

In this case, we randomly select 90 percent of the enhancive and degressive interactions. For the testing set, we consider the remaining 10 percent of the enhancive and degressive interactions. In the first case of the testing procedure, the model was selected, and some hyper-parameters, such as the number of epochs, were determined. Figure 5, shows the training process for the selected model. As expected, the model's accuracy is strict on ascending training data, but there are ups and downs for testing data after Epoch 5. In the loss function graph, by the end of epoch 5, as the epochs increase, the loss function's value on training and testing procedure decreases. After epoch 5, the trend of training data continues, but the testing trend is reversed. In other words, over fit occurs. Therefore, based on the graphs, the appropriate number of epochs in this step was considered 5.



Hyperparameters Optimization

Keep in mind that network's hyperparameters are not optimized, and the specified parameters are not necessarily at their best. There are two reasons for not optimizing hyperparameters:

1) Model overfitting: If hyperparameters changed to the best values, it is expected that the model will get better results on the present data, but there is no guarantee that the extracted features by the model are significant and works well when used in new cases. In this case, the so-called model is over-fitted and will be a negative point for the model.

2) Robustness: Optimal hyperparameters give better results for the present data, but different drug similarities may be used in the future, or new data may be collected, and the present results may not be repeated. In this case, the model loses its robustness and will not be accepted in the pharmaceutical and pharmacological community.

Evidence of reliability of the two-class model

Finally, we examine the results of the proposed model in the 10-fold CV from three views:

1) Model Resolution: In a 10-fold CV, the model obtained $AUC = 0.97$, $AUPR = 0.93$ for degressive interactions, and $AUC = 0.97$, $AUPR = 0.99$ for enhansive interactions. These results indicate the high resolution and detection power of the selected model. The selected model resolution results are presented in Table 2 which identifies the type of degressive and enhansive interactions.

	Precision	Recall	F-measure	Accuracy	Support
Degressive	0.94	0.83	0.88		850
Enhansive	0.95	0.99	0.97		3052
Macro Avg	0.95	0.91	0.93	0.95	3902
Weighted Avg	0.95	0.95	0.95	0.95	3902

Table 2 Interaction type classification report

Table 2 is an example result of implemented model which shows the ability of the model in terms of precision, recall and F-measure. Indicates the type of interactions. According to Table 2 the precision of the model in detecting enhansive and degressive interactions is 95 percent and 94 percent, while recall is 99 percent and 83 percent, respectively. the F-measure is also 97 percent and 88 percent that the higher ability of the model to detect degressive interactions comes from a higher number of these types of interactions. The ratio of degressive interaction to enhansive interaction is approximately 4 to 1.

2) Variance: The confidence interval for the reported values with a reliability coefficient above 95 percent was narrow and close to each other. Out of four reported confidence interval values, three values were less than ± 0.002 , and only for the degressive interaction, the AUPR was in the range of ± 0.005 . The low amount of variance obtained from the model shows that the proposed model is robust.

3) Separability: By plotting the output probability distribution diagram, as shown in Figure 6, it is clear that values +1 and -1 are well separated, and probability distribution degressive and enhansive have slightly Subscriptions.

The Suducode 1 shows the step-by-step model selection process.

Algorithm 1 Model selection suducode

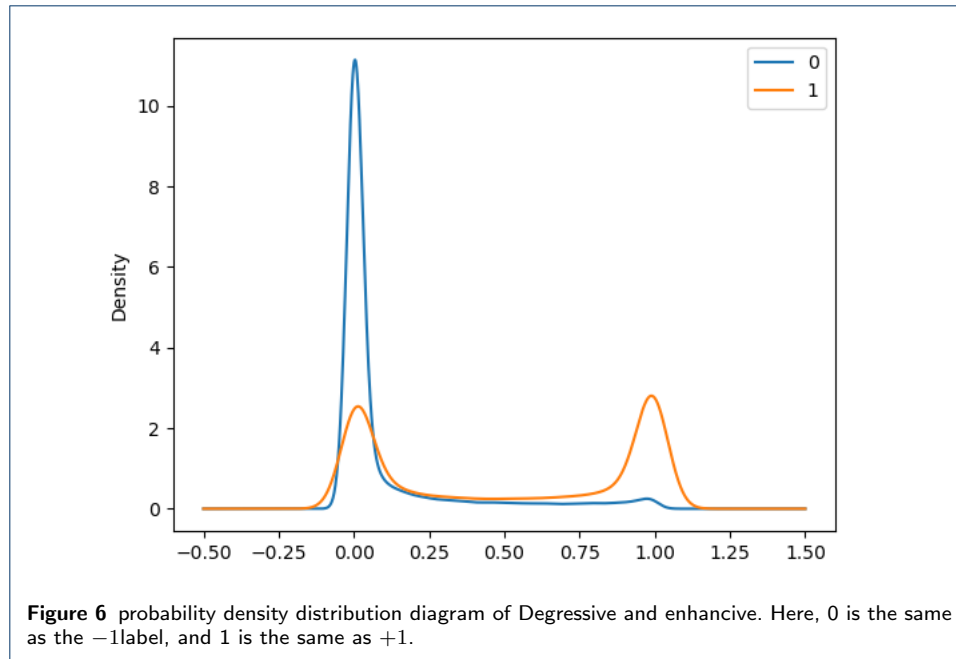
Input: +1 and -1 drug pairs features

Output: +1 and -1 diagnostic model

- 1: Apply 10-fold CV to the features of +1 and -1 drug pairs.
 - 2: Select the right model.
 - 3: Test the model results in 10-fold CV.
 - 4: If 3 is correct then select the model, else go to 2.
-

Detecting of non-interaction drug pairs

In the previous step, a high-precision, robust, and accurate model has been presented to detect drug pairs' potential interactions for both degressive and enhansive.



Therefore, this model has the ability to detect non-interactions (real zeros) as follows. If drug pairs are unlikely to interact, then those drug pairs are likely to be real zeros.

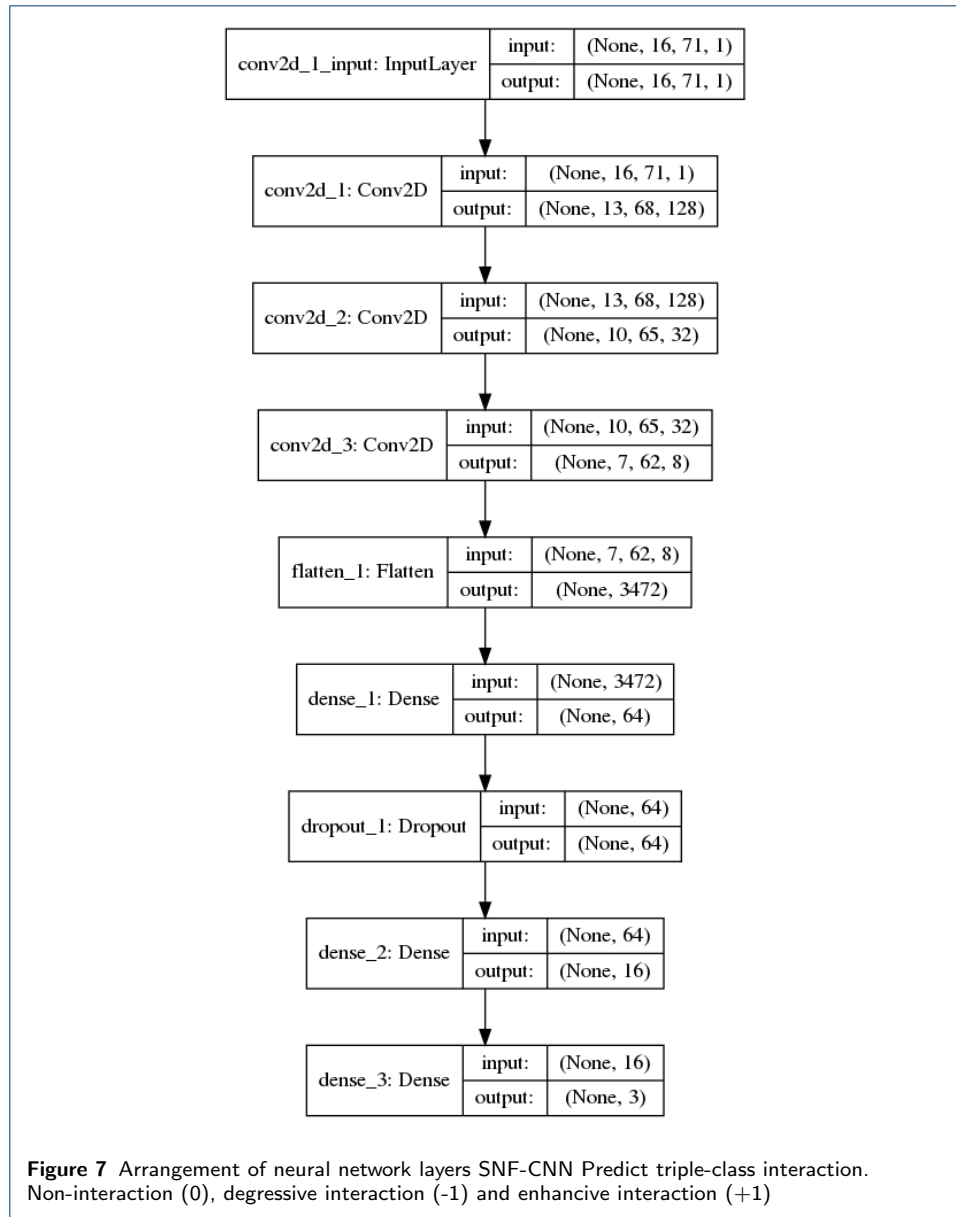
According to this hypothesis, the model was used to predict all unknown drug pairs (zeros). Unknown drug pairs include 270,000 drug pairs. We consider drug pairs as non-interacting drug pairs in the model's output if the enhanceive and degressive probability are less than 0.4 and 0.4. Among the unlabeled data, about 65,000 drug pairs had these conditions. These drug pairs are candidates for non-interaction. Due to the model's high accuracy, the low variance of results, and the model's high resolution, we consider these pairs non-interaction drug pairs.

Selecting and training model on known and unknown interactions

This section uses known data and potential non-interaction candidates to form a data set. Here, we use the non-interaction candidate drug pairs as real zeros. The recommender system presented in Section Selecting model is also used for the final model.

First, the B matrix rows, which contain the $+1$ and -1 interactions, are separated according to the previously detailed procedure and placed in 10 parts. Then, 30,000 non-interacting candidate drug pairs were randomly selected from 65,000 drug pairs. In the chosen drug pairs, the drug pairs and the dual of them must be non-interaction candidates. The zeros group is randomly divided into 10 parts, so each drug pairs and the dual are in the same batch. Then 10 parts of zeros are merged with 10 parts of pre-prepared $+1$ s and -1 s.

The data set contains approximately 72,702 drug pairs, divided into relatively equal parts, is ready to use in the training and testing of the final recommender system.



Selecting final model

The final model is almost the same as that described in Section Selecting model . That means it has three Conv-layer with 128, 32, and 8 filters. Then, as before, three fully connected Conv layers were used. The difference was that the number of nodes changed from 64, 16 and 2 to 64, 16, and 3 in each layer, respectively. Specifically, this model gives three possible outputs for the three modes of enhancive interaction, non-interaction, and depressive interaction. Also, the number of epochs was considered 9. The deep neural network model for predicting interaction is shown in Figure 7. At this stage, the new model was not chosen because:

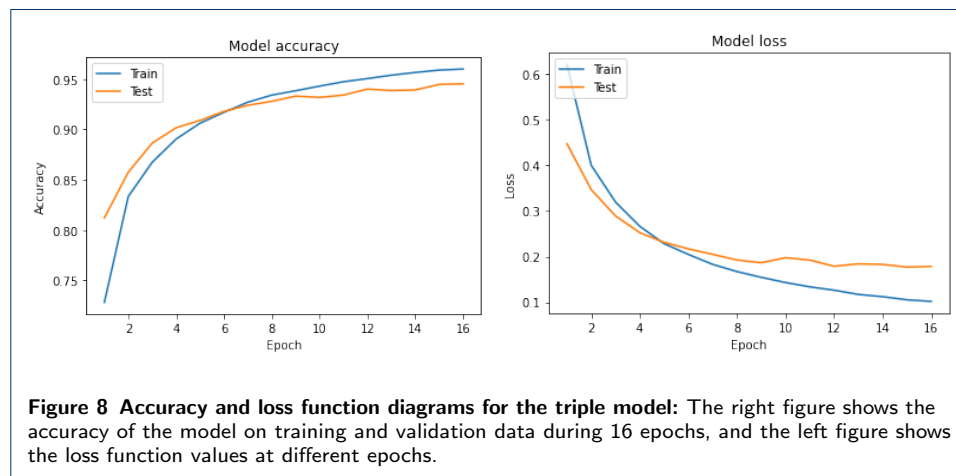
- 1) The power of this model for relatively accurate detection of enhancive and depressive interactions has been proven.

2) The zeros used in this section are just suggested and have not been approved by the Pharmacology Laboratory. Until the writing of this article, a comprehensive database for non-interaction cases has not been made public. If the model selection is made again, a model may be selected that is not necessarily valid in real-world application and hard to accept.

Due to the above reasons, the zeros recommender system is used to comprehensive drug-drug interactions prediction by changing the number of outputs from 2 to 3 as the input data.

Three-class model's training trend

In this case, we divide the set of all interactions (enhancive, degressive, and zeros of the first step) into 10 equal parts. We consider one part of the testing set and the other 9 parts as the training data set. Divide all the zeros in the previous step into 10 parts and add a 1 to 9 ratio to both testing and training sets. In the second case, the previous model's 10-fold CV procedure was trained with the least changes to predict the three classes. Besides, hyper-parameter, the number of epochs was determined. Figure 8 shows the training process. The process of the accuracy of the model on training data increases steadily with the increase of epochs. Still, the model after epoch 9 reduces a constant and decreases the accuracy a little for testing data.



The proposed SNF-CNN method's general process is presented in the form of pseudocode 2, which includes the steps of preparation, model selection, real zero detection, and the presentation of a comprehensive recommender system.

Results and discussion

Each setting of model and features and each data set needs its own validation process. According to the type of problem and the methods, we use two types of 10-fold CV to select the most proper model also to validate the results of the chosen model. The metrics which are used in validation are described in following.

Evaluation criteria for final three-class model

In this study, we classify drug pairs into three classes, according to the type of interaction or non-interaction, so in order to compare the method performance

Algorithm 2 Final model selection(SNF-CNN) sudocode**Input:** Drug pairs features(+1,-1,real 0)**Output:** Diagnostic model for interaction and non-interaction

- 1: Calculate drug similarity matrices with the cosine method.
- 2: Integrate drug similarity matrices with the similarity network fusion(SNF) method.
- 3: Built the input matrix of the model.
- 4: Select the fit known interactions model and train it.
- 5: Predict probable zeros by using step 4.
- 6: Select the fit known interactions and zeros of step 5 model , and train it.
- 7: Predict on unknown drug pairs.

with other existing methods, four measurement criteria, F- measure, accuracy, Area Under Roc Curve(AUC), and Area Under Precision-Recall Curve(AUPR) are Used. To define these criteria, we should use a confusion matrix as Table 3.

	Actual Enhanceive	Actual Degressive	Actual Non-interaction
Predicted Enhanceive	$T_{Enh} - cell_1$	$F_{Enh} - cell_2$	$F_{Enh} - cell_3$
Predicted Degressive	$F_{Deg} - cell_4$	$T_{Deg} - cell_5$	$F_{Deg} - cell_6$
Predicted Non-interaction	$F_{NonInt} - cell_7$	$F_{NonInt} - cell_8$	$T_{NonInt} - cell_9$

Table 3 The confusion matrix and relevant evaluation index for predicting triple classes whose cell names start with T (True). The main diagonal amounts of the matrix show correct predictions for each class. The other cells show drug pairs that have been classified by mistake whose cell names start with F (False).

Table 3 shows the confusion matrix for the triple class case. In this mode, we have to redefine the definitions of TP, TF, TN, and TP, as well as accuracy, precision, recall, and F- measure.

$Accuracy_{(enh/deg/nonInt)}$: The fraction of all correct predictions (TPs) to all predictions.

$$Accuracy = \frac{\text{All correctly predicted } (cell_1 + cell_5 + cell_9)}{\text{All nine cells } (\sum_{i=1}^9 cell_i)}$$

Base on Table 3 TP, TF, TN, and TP will define as Table 4.

The other three evaluation criteria for each class are defined as follows:

Precision: The fraction of correct predicted ($TP_{enh/deg/nonInt}$) interactions among all predicted (enh/deg/nonInt) interactions.

$$Precision_{(enh/deg/nonInt)} = \frac{TP}{TP + FP}$$

Enhancive	Degressive	Non-interaction
TP = $cell_1$	TP = $cell_5$	TP = $cell_9$
FP = $cell_2 + cell_3$	FP = $cell_4 + cell_6$	FP = $cell_7 + cell_8$
FN = $cell_4 + cell_7$	FN = $cell_2 + cell_8$	FN = $cell_3 + cell_6$
TN = $cell_5 + cell_6 + cell_8 + cell_9$	TN = $cell_1 + cell_3 + cell_7 + cell_9$	TN = $cell_1 + cell_2 + cell_4 + cell_5$

Table 4 The new definition of TP, TN, FP, and FN in the triple class mod.

Recall: The fraction of correct predicted ($TP_{enh/deg/nonInt}$) interactions among all true (enh/deg/nonInt) interactions.

$$\text{Recall}_{(enh/deg/nonInt)} = \frac{TP}{TP + FN}$$

Precision and recall for each class have a trade-off; Therefore, F-measure can show resolution ability of model in each class.

F-measure: The geometric mean of precision and recall in three-class:

$$F - \text{measure}_{(enh/deg/nonInt)} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Also, we evaluated methods via modified AUC, and AUPR for three-class model.

Comparison of results

Based on the validation procedure, which described in Section , the binary interaction type detection model is devised and trained. Then, the final three-class model is presented which took the most probable non-interactions as zeros. The SNF-CNN model is evaluated in 10- fold CV to check the robustness, and efficiency of the SNF-CNN. Results of SNF-CNN and other methods for comparison are presented and discussed in this section.

	Precision	Recall	F-measure	Accuracy	Support
Enhancive	0.88	0.84	0.86		850
Non-intraction	0.96	0.95	0.96		3000
Degressive	0.95	0.97	0.96		3052
Macro Avg	0.93	0.92	0.93	0.95	6902
Weighted Avg	0.95	0.95	0.95	0.95	6902

Table 5 Three-Classes interaction classification report

Table 5 three-class interaction classification is displayed. In this implementation, the precision of the model in detecting degressive interactions, non-interactions, and enhancive interactions are 95%, 96%, and 88%, respectively. The recalls are 97%, 95%, and 84%, respectively, and finally, F-measures are 96%, 96%, and 86%. The model power in the three-classes mode decreases slightly in comparison to the two-classes which can be due to two reasons.

- 1) The problem of three-classes is more difficult than two-classes, obviously.
- 2) The suggested non-interactions or zeros are not necessarily real and are not pharmacologically proven, so there is a possibility of some disturbance.

For the above reasons, the detection ability reduction of the three-classes model was not unexpected.

	AUC	AUPR
degressive	0.9747 ± 0.0033	0.9666 ± 0.0045
enhancive	0.9686 ± 0.0028	0.8221 ± 0.0184
non-interaction	0.9714 ± 0.0040	0.9480 ± 0.0083

Table 6 Results of SNF-CNN algorithm in predicting three-classes based on AUC and AUPR criteria and their confidence interval

Since the previous three-classes DDI models reported AUC and AUPR for comparison, so SNF-CNN results which are shown in Table 6 are reported based on these two criteria. Also, the margin of error with the 95% confidence interval is reported in Table 6. The algorithm results have a small margin in the 10- fold CV which shows the robustness and reliability of the proposed algorithm.

	AUC	AUPR
SNF-CNN	0.971	0.912
BRSNMF [35]	0.805	0.644
Semi-NMF [33]	0.796	0.579
TMFUF [32]	0.842	0.526

Table 7 Comparison of the results of three-classes prediction algorithms based on criteria AUC and AUPR

In Table 7 results of SNF-CNN averaged for the three classes and compared with other existing three-classes algorithms. According to Table 7, the proposed algorithm has a high difference compared to other superior algorithms with the problem of ternary and has been able to challenge other algorithms.

Conclusions

Existing machine learning approaches are able to detect potential interactions of a drug by using large-scale data before taking the drug. However, they cannot predict comprehensive three-class DDIs, including degressive and enhancive interactions. It is more informative to clarify if a drug pair has an enhancive DDI or a degressive DDI or even non-DDI than recognizing a drug pair whether or not has DDI. Without considering the pharmacological changes caused by DDIs, most existing approaches only report two-classes predictions. In addition, not only the occurrence of degressive and enhancive DDIs is not random, but also it represents a piece of information about those major behavior of those two drugs. None of the existing approaches investigates and considers this intrinsic important property of interactions when treating complex diseases [34].

In this work, after representing comprehensive DDI data and drug features, we used the template of recommender systems to design a novel algorithm. Although the prediction obtained by our algorithm was inspiring, overall performance could still be improved. So we investigated those incorrectly predicted DDIs. To prove the algorithm in practice we checked case-by-case of the model predictions, in the

latest version of the DrugBank database. Observations and investigations led to the discovery of three reasons for wrong predictions:

1) The first is about removed interactions in DrugBank version 5 which are precisely labeled as DDIs in DrugBank version 4. For example, the old version of DrugBank records that Apraclonidine (DB00964) (also known as iopidine, is a sympathomimetic used in glaucoma therapy.) increases the atrioventricular blocking activities of Alprenolol (DB00866) and Bevantolol (DB01295), while the newer version removes them, so new research show they have no interaction.

2) The second one is about drug Pairs which are labeled as non-DDIs in DrugBank version 4, but in the current version, they are reported as DDIs. For example, the pair of Valrubicin (DB00385) and Cyclosporine (DB00091), as well as the pair of Ergocalciferol (DB00153) and Calcitriol (DB00136) in the newer version of DrugBank, reports, Valrubicin (bladder cancer treatment drug) Increases the activity of the nephrotoxic drug Cyclosporine(A drug that suppresses the immune system with a special action on T-lymphocytes), while the combined therapy of Calcitriol and Ergocalciferol increases the risk or severity of adverse effects in the multiple-drug therapy.

3) The last one refers to altering DDIs' types, which are labeled as enhancive DDIs in DrugBank version 4, but in the current version, are labeled as degressive DDIs, and vice versa.

We expect that the SNF-CNN approach will be able to achieve better results in DDI prediction by a better dataset that has less missed or false information about drug pairs. For future work, it is recommended that drugs and their features always be collected from the latest version of DrugBank.

Three-classes data is an attempt to improve expression and problem solving over two-classes data. However, three-classes data does not have sufficient biological significance and provides limited biological information. This means that predicting the type of DDI can be useful, but it is not clear at what stage of the pharmacokinetic or pharmacodynamic stages this DDI occurred. Therefore, it is suggested to collect datasets with degressive and enhancive labels from each of the pharmacokinetic and pharmacodynamic steps. In this case, more meaningful models in terms of pharmacology and machine learning may be designed and built. Results from these models will more important to pharmacists and will be more useful for further steps with human health aim.

Appendix

Text for this section. . .

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Text for this section. . .

Abbreviations

DDI:Drug-drug interactions; CV:cross-validation; SNF:Similarity Network Fusion;

Availability of data and materials

the code and data is available at GitHub page of [SNF-CNN code and data](#)

Ethics approval and consent to participate

The authors declare that they have consenting to participate.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

The authors declare that they have consenting to publication.

Authors' contributions

BI conceived and designed the experiments, draft the manuscript, and analyzed the results. MAK contributed materials/analysis tools and developed the codes used in the analysis. CE is the corresponding author. All authors read and approved the final manuscript.

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References

- Wienkers, L.C., Heath, T.G.: Predicting in vivo drug interactions from in vitro drug discovery data. *Nature reviews Drug discovery* **4**(10), 825–833 (2005)
- Law, V., Knox, C., Djoumbou, Y., Jewison, T., Guo, A.C., Liu, Y., Maciejewski, A., Arndt, D., Wilson, M., Neveu, V., et al.: Drugbank 4.0: shedding new light on drug metabolism. *Nucleic acids research* **42**(D1), 1091–1097 (2014)
- Leape, L.L., Bates, D.W., Cullen, D.J., Cooper, J., Demonaco, H.J., Gallivan, T., Hallisey, R., Ives, J., Laird, N., Laffel, G., et al.: Systems analysis of adverse drug events. *Jama* **274**(1), 35–43 (1995)
- Businaro, R.: Why we need an efficient and careful pharmacovigilance? *Journal of pharmacovigilance* (2013)
- Karbownik, A., Szałek, E., Sobańska, K., Grabowski, T., Wolc, A., Grześkowiak, E.: Pharmacokinetic drug-drug interaction between erlotinib and paracetamol: a potential risk for clinical practice. *European Journal of Pharmaceutical Sciences* **102**, 55–62 (2017)
- Mulroy, E., Highton, J., Jordan, S.: Giant cell arteritis treatment failure resulting from probable steroid/antiepileptic drug-drug interaction. *The New Zealand Medical Journal (Online)* **130**(1450), 102 (2017)
- Zhao, X.-M., Iskar, M., Zeller, G., Kuhn, M., Van Noort, V., Bork, P.: Prediction of drug combinations by integrating molecular and pharmacological data. *PLoS Comput Biol* **7**(12), 1002323 (2011)
- Veith, H., Southall, N., Huang, R., James, T., Fayne, D., Artemenko, N., Shen, M., Inglese, J., Austin, C.P., Lloyd, D.G., et al.: Comprehensive characterization of cytochrome p450 isozyme selectivity across chemical libraries. *Nature biotechnology* **27**(11), 1050–1055 (2009)
- Huang, S.-M., Temple, R., Throckmorton, D., Lesko, L.: Drug interaction studies: study design, data analysis, and implications for dosing and labeling. *Clinical Pharmacology & Therapeutics* **81**(2), 298–304 (2007)
- Zhang, P., Wang, F., Hu, J., Sorrentino, R.: Label propagation prediction of drug-drug interactions based on clinical side effects. *Scientific reports* **5**(1), 1–10 (2015)
- Wiśniowska, B., Polak, S.: The role of interaction model in simulation of drug interactions and qt prolongation. *Current pharmacology reports* **2**(6), 339–344 (2016)
- Zhou, D., Bui, K., Sostek, M., Al-Huniti, N.: Simulation and prediction of the drug-drug interaction potential of naloxegol by physiologically based pharmacokinetic modeling. *CPT: pharmacometrics & systems pharmacology* **5**(5), 250–257 (2016)
- Bui, Q.-C., Sloot, P.M., Van Mulligen, E.M., Kors, J.A.: A novel feature-based approach to extract drug–drug interactions from biomedical text. *Bioinformatics* **30**(23), 3365–3371 (2014)
- Zhang, Y., Wu, H.-Y., Xu, J., Wang, J., Soysal, E., Li, L., Xu, H.: Leveraging syntactic and semantic graph kernels to extract pharmacokinetic drug drug interactions from biomedical literature. *BMC systems biology* **10**(3), 67 (2016)
- Yamanishi, Y., Araki, M., Gutteridge, A., Honda, W., Kanehisa, M.: Prediction of drug–target interaction networks from the integration of chemical and genomic spaces. *Bioinformatics* **24**(13), 232–240 (2008)
- Vilar, S., Uriarte, E., Santana, L., Lorberbaum, T., Hripcsak, G., Friedman, C., Tatonetti, N.P.: Similarity-based modeling in large-scale prediction of drug-drug interactions. *Nature protocols* **9**(9), 2147 (2014)
- Cheng, F., Zhao, Z.: Machine learning-based prediction of drug–drug interactions by integrating drug phenotypic, therapeutic, chemical, and genomic properties. *Journal of the American Medical Informatics Association* **21**(e2), 278–286 (2014)
- Pahikkala, T., Airola, A., Pietilä, S., Shakyawar, S., Szajda, A., Tang, J., Aittokallio, T.: Toward more realistic drug–target interaction predictions. *Briefings in bioinformatics* **16**(2), 325–337 (2015)
- Luo, H., Zhang, P., Huang, H., Huang, J., Kao, E., Shi, L., He, L., Yang, L.: Ddi-cpi, a server that predicts drug–drug interactions through implementing the chemical–protein interactome. *Nucleic acids research* **42**(W1), 46–52 (2014)
- Shi, J.-Y., Huang, H., Li, J.-X., Lei, P., Zhang, Y.-N., Yiu, S.-M.: Predicting comprehensive drug-drug interactions for new drugs via triple matrix factorization. In: *International Conference on Bioinformatics and Biomedical Engineering*, pp. 108–117 (2017). Springer
- Liu, S., Chen, K., Chen, Q., Tang, B.: Dependency-based convolutional neural network for drug-drug interaction extraction. In: *2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pp. 1074–1080 (2016). IEEE
- Ryu, J.Y., Kim, H.U., Lee, S.Y.: Deep learning improves prediction of drug–drug and drug–food interactions. *Proceedings of the National Academy of Sciences* **115**(18), 4304–4311 (2018)
- Wang, B., Mezlini, A.M., Demir, F., Fiume, M., Tu, Z., Brudno, M., Haibe-Kains, B., Goldenberg, A.: Similarity network fusion for aggregating data types on a genomic scale. *Nature methods* **11**(3), 333 (2014)
- Olayan, R.S., Ashoor, H., Bajic, V.B.: Ddr: efficient computational method to predict drug–target interactions using graph mining and machine learning approaches. *Bioinformatics* **34**(7), 1164–1173 (2018)

25. Tian, Z., Guo, M., Wang, C., Xing, L., Wang, L., Zhang, Y.: Constructing an integrated gene similarity network for the identification of disease genes. *Journal of biomedical semantics* **8**(1), 32 (2017)
26. Kim, Y.-A., Cho, D.-Y., Przytycka, T.M.: Understanding genotype-phenotype effects in cancer via network approaches. *PLoS computational biology* **12**(3), 1004747 (2016)
27. Wang, Y., Liu, T., Xu, D., Shi, H., Zhang, C., Mo, Y.-Y., Wang, Z.: Predicting dna methylation state of cpg dinucleotide using genome topological features and deep networks. *Scientific reports* **6**, 19598 (2016)
28. Huang, Q.-R., Hu, F., Huang, S., Li, H.-X., Yuan, Y.-H., Pan, G.-X., Zhang, W.-J., et al.: Effect of long-term fertilization on organic carbon and nitrogen in a subtropical paddy soil. *Pedosphere* **19**(6), 727–734 (2009)
29. Fu, L., Peng, Q.: A deep ensemble model to predict mirna-disease association. *Scientific reports* **7**(1), 1–13 (2017)
30. Pan, X., Fan, Y.-X., Yan, J., Shen, H.-B.: Ipmminer: hidden ncRNA-protein interaction sequential pattern mining with stacked autoencoder for accurate computational prediction. *BMC genomics* **17**(1), 582 (2016)
31. Koch-Weser, J.: Serum drug concentrations in clinical perspective. *Therapeutic drug monitoring* **3**(1), 3–16 (1981)
32. Shi, J.-Y., Huang, H., Li, J.-X., Lei, P., Zhang, Y.-N., Dong, K., Yiu, S.-M.: Tmfuf: a triple matrix factorization-based unified framework for predicting comprehensive drug-drug interactions of new drugs. *BMC bioinformatics* **19**(14), 27–37 (2018)
33. Yu, H., Mao, K.-T., Shi, J.-Y., Huang, H., Chen, Z., Dong, K., Yiu, S.-M.: Predicting and understanding comprehensive drug-drug interactions via semi-nonnegative matrix factorization. *BMC systems biology* **12**(1), 14 (2018)
34. Cokol, M., Kuru, N., Bicak, E., Larkins-Ford, J., Aldridge, B.B.: Efficient measurement and factorization of high-order drug interactions in mycobacterium tuberculosis. *Science advances* **3**(10), 1701881 (2017)
35. Shi, J.-Y., Mao, K.-T., Yu, H., Yiu, S.-M.: Detecting drug communities and predicting comprehensive drug-drug interactions via balance regularized semi-nonnegative matrix factorization. *Journal of cheminformatics* **11**(1), 1–16 (2019)
36. Camacho, L.A.G., Alves-Souza, S.N.: Social network data to alleviate cold-start in recommender system: A systematic review. *Information Processing & Management* **54**(4), 529–544 (2018)
37. Zhang, W., Chen, Y., Tu, S., Liu, F., Qu, Q.: Drug side effect prediction through linear neighborhoods and multiple data source integration. In: 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 427–434 (2016). IEEE
38. Zhang, W., Chen, Y., Li, D., Yue, X.: Manifold regularized matrix factorization for drug-drug interaction prediction. *Journal of biomedical informatics* **88**, 90–97 (2018)
39. Ross Markello: snfpy 0.2.2 (2018). <https://pypi.org/project/snfpy/> Accessed Accessed 20 October 2020
40. Nair, V., Hinton, G.E.: Rectified linear units improve restricted boltzmann machines. In: ICML (2010)
41. Hinton, G., Deng, L., Yu, D., Dahl, G.E., Mohamed, A.-r., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T.N., et al.: Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal processing magazine* **29**(6), 82–97 (2012)
42. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R.: Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research* **15**(1), 1929–1958 (2014)
43. Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., et al.: Tensorflow: A system for large-scale machine learning. In: 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16), pp. 265–283 (2016)
44. Chollet, F., et al.: Keras. <https://github.com/fchollet/keras>
45. Ghosal, T., Edithal, V., Ekbal, A., Bhattacharyya, P., Chivukula, S.S.S.K., Tsatsaronis, G.: Is your document novel? let attention guide you. an attention based model for document level novelty detection. *Natural Language Engineering* **1**(1), 1–38 (1997)
46. Toda, Y., Okura, F.: Research article how convolutional neural networks diagnose plant disease. *Challenge (LSVRC)*, 20 (2012)
47. Seen, S.: 1-day learning, 1-year localization: Long-term lidar localization using scan context image. *Database* **2012**, 01–15 (2012)
48. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014)

Figures

Tables

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