Leveraging Sentence-BERT for Advanced MicroRNA Target Predictions in Diseases

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Abstract

MicroRNAs (miRNAs) regulate gene expression by binding to mRNAs, inhibiting translation, or promoting mRNA degradation. miRNAs are of great importance in the development of diseases. Currently, a variety of miRNA target prediction tools are available, which analyze sequence complementarity, thermodynamic stability, and evolutionary conservation to predict miRNA-target interactions (MTIs) within the 3' untranslated region (3'UTR). We propose a further screening method for sequence-based predicted MTIs by considering the disease semantic similarity between miRNA and gene to establish a prediction database of disease-specific MTIs. We fine-tuned a Sentence-BERT model to calculate disease semantic similarity. The method achieves a recall of 91% on the validation dataset, which comprises intersecting MTIs from miRTarBase and miRWalk that represent experimentally verified predicted MTIs. Additionally, the method demonstrates excellent generalizability across different databases. The proposed method was utilized to calculate the semantic similarity of diseases in 3,900,041 experimentally validated and predicted MTIs, involving 7,727 genes and 1,263 miRNAs. The observed distribution of similarity aligns perfectly with existing biological evidence. The study holds the potential to offer valuable insights into comprehending miRNA-gene regulatory networks and advancing progress in disease diagnosis, treatment, and drug development.

1 Introduction

In 1993, miRNA (Lin-4) was first discovered and found to be critical for the timing of embryonic development in C. elegans [1]. Since then, a large number of miRNAs have been discovered with the development of high-throughput bioinformatics technologies [2]. miRNAs are classified as small non-coding RNAs (ncRNAs), play a crucial role in the regulation of various physiological processes, such

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as cell cycle [3], cell growth, development, differentiation, and apoptosis [4], as well as pathological processes [5]. In addition, miRNAs may be promising biomarker candidates for early detection or prognosis of various diseases [6]. Therefore, the identification of MTIs in diseases holds biological significance.

There are many existing MTIs prediction databases. miRWalk identify consecutive complementary subsequences between miRNA and gene, as well as 8 other algorithms, to construct a database for MTIs prediction in different species [7]. miRDB considered miRNA overexpression (target downregulation) and CLIP-seq data (miRNA binding), utilizing a support vector machine (SVM) for the prediction of MTIs in different species [8]. mirSVR trained a regression model to rank miRNA target sites based on down-regulation score, using data from miRanda [9]. DeepTarget uses Recurrent Neural Networks (RNN) for sequence-sequence interaction learning to predict MTIs [10]. TargetScan predicts MTIs based on seed match and conservativeness analysis in different species [11]. The RNA22 is designed for the identification of miRNA binding sites and their corresponding miRNA and mRNA complexes [12]. PITA predicts miRNA targets by considering both the binding free energy and the accessibility of the target site within the mRNA secondary structure [13]. StarBase explores miRNA-mRNA and miRNA-lncRNA interaction networks based on CLIP-Seq data [14]. However, there are few disease-specific MTIs prediction databases.

The NLP method can be employed to address this issue. The Sentence-BERT (SBERT) enhances the pre-trained BERT network by incorporating siamese and triplet network structures. The SBERT model demonstrates excellent performance in semantic similarity tasks [15]. Moreover, the SBERT has a faster speed compared to BERT [16] and RoBERTa [17] while maintaining accuracy.

The present study proposes a method for calculating the similarities of diseases between miRNAs and genes, aiming to further screen sequence-based predicted MTIs to establish a prediction database of disease-specific MTIs. We assume that MTIs exhibiting higher disease similarity are more likely to encounter in tissues and classified as Functional MTIs. The experiment result confirms this hypothesis. The similarity between two diseases can be derived using the SBERT model. Then utilize clustering to group miRNA-associated diseases and gene-associated diseases based on disease similarities, followed by the calculation of either the intra-cluster mean or overall mean to obtain disease similarity between miRNA and gene.

2 Materials and Methods

2.1 Overview

We present a flow chart (Figure 1) that outlines our study's major steps. The steps encompass fine-tuning the SBERT model, utilizing clustering for computing disease similarity between miRNAs and genes, and classifying MTIs based on disease similarity.

2.2 Data Collection

To fine-tune the SBERT model, we downloaded the MeSH (Medical Subject Headings) descriptors (https://meshb.nlm.nih.gov/) from the National Library of Medicine. The MeSH descriptors are standardized terms utilized for indexing and

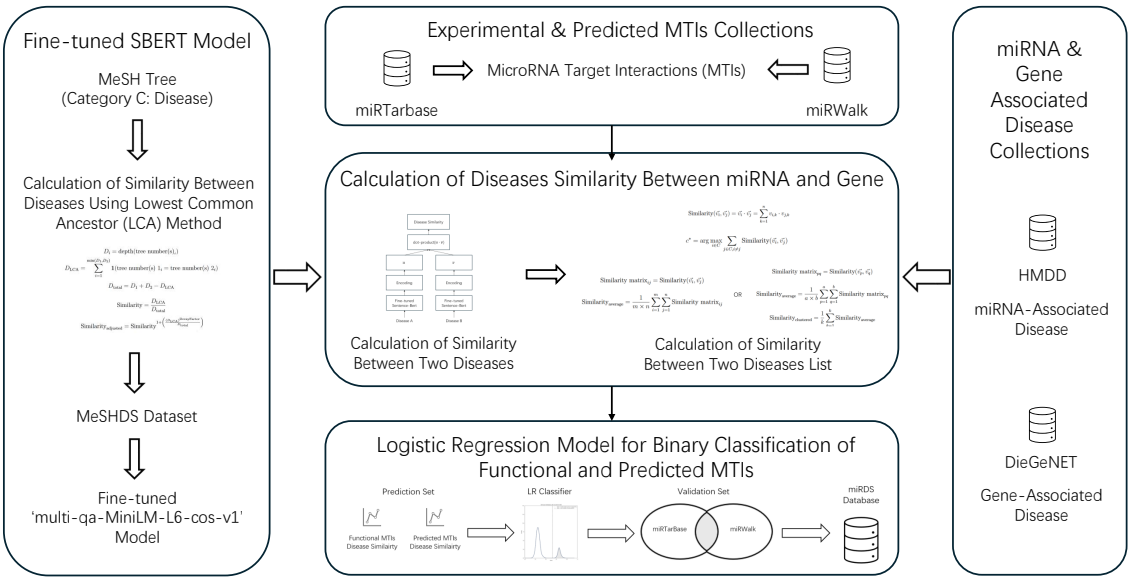


Figure 1: Flow Chart

retrieving biomedical and health-related information, forming a hierarchical vocabulary tree (Figure 2). To test the SBERT model performance, we obtained the BIOSSES dataset, which consists of 100 pairs of biomedical statements with manually annotated text similarity scores provided by experts [18]. It can be used to evaluate text similarity calculation models in the field of biomedicine. To obtain experimentally verified and predicted MTIs, we utilized the miRTarBase [19] and miRWalk [7]. miRTarBase provides experimentally validated MTIs. The MTIs are primarily categorized into two groups: Functional MTIs and Functional MTIs (Weak). Functional MTIs are validated through Reporter assays or Western blot, as well as other sensitive and specific techniques. Functional MTIs (Weak) are identified using Microarray, qPCR, or sequencing. miRWalk provides sequenced-based predicted MTIs. We processed the miRTarBase and miRWalk data by merging the -3p and -5p of the same miRNA. For acquiring information on miRNA-associated and gene-associated diseases, we employed HMDD [20], DisGeNet [21] and KEGG [22]. HMDD offers miRNA-associated disease data. DisGeNet and KEGG offer gene-associated disease data, for each gene, we selected its top 40 most relevant diseases.

2.3 Model Construction

2.3.1 Fine-tuned SBERT Model for Disease Semantic String Analysis

For the model to have the ability to handle the disease semantic string similarity computation task while maintaining its original performance, we utilized the MeSH descriptors category C (diseases) to generate a disease semantic string similarity dataset to fine-tune the model. The disease similarity distribution in the dataset we created is similar to the disease semantic similarity distribution output by the 'sentence-transformers/multi-qa-MiniLM-L6-cos-v1' [23] model without fine-tuning. Both types of distributions follow a log-normal distribution pattern. The methods are as follows:

- Determine the depth of the disease descriptors in the MeSH Tree:

$$D_i = \text{depth}(\text{tree number(s)}_i) \tag{1}$$

- Determine the depth of the lowest common ancestor (LCA) between two disease descriptors:

$$D_{\text{LCA}} = \sum_{i=1}^{\min(D_1,D_2)} \mathbf{1}(\text{tree number(s) } 1_i = \text{tree number(s) } 2_i) \tag{2}$$

  Parameter Definitions: tree number(s)1_i = tree number(s)2_i indicates the level at which the two diseases share a common node in their hierarchical structure. i ranges from 1 to the depth at which the two codes' lowest common ancestor (LCA) of the two tree numbers is located.

- Calculate the total depth:

$$D_{\text{total}} = D_1 + D_2 - D_{\text{LCA}} \tag{3}$$

- Calculate the disease similarity:

$$\text{Similarity} = \frac{D_{\text{LCA}}}{D_{\text{total}}} \tag{4}$$

- Calculate the adjusted disease similarity:

$$\text{Similarity}_{\text{adjusted}} = \text{Similarity}^{1+\left(\frac{(D_{\text{LCA}})^{\text{DecayFactor}}}{D_{\text{total}}}\right)} \tag{5}$$

The decay factor of 0.8 was selected in this paper. According to the provided formula, the weighted disease similarity between the descriptor: Cardiovascular Infections, tree number(s): C14.260, and the descriptor: Out-of-Hosptial Cardiac Arrest, tree number(s): C14.280.383.610 is 0.14495593273553914 (Figure 2, Figure 3) . The weighted disease similarity was further adjusted to better align with the distribution of the output generated by the 'multi-qa-MiniLM-L6-cos-v1' model, resulting in a dataset, named 'MeSHDS'. We utilized this dataset to fine-tune the SBERT model.

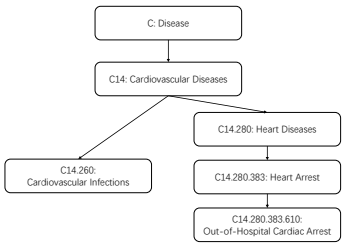


Figure 2: Disease Descriptor 'Cardiovascular Infections' and 'Out-of-Hospital Cardiac Arrest' Hierarchical Structure in MeSH Tree

$D_{\text{Cardiovascular Infections}} = 2,$
$D_{\text{Out-of-Hospital Cardiac Arrest}} = 4,$
$D_{\text{LCA}} = 1,$
$D_{\text{total}} = 5,$
$\text{Similarity} = 0.2,$
$\text{Similarity}_{\text{adjusted}} = 0.14495593273553914$

Figure 3: Adjusted Similarity Calculation between 'Cardiovascular Infections' and 'Out-of-Hospital Cardiac Arrest'

2.3.2 Disease Similarity Calculation Between miRNAs and Genes

To calculate the disease similarity between miRNA and gene. We propose an algorithm to compute the similarity of two lists of disease strings. The algorithm combines semantic string similarity calculation and clustering.

Semantic String Encoding and Similarity Calculation First, each string in the list is encoded using the Sentence-BERT model. The similarity between two semantic strings is obtained by calculating the dot product of their encoding vectors:

$$\text{Similarity}(\vec{v_i}, \vec{v_j}) = \vec{v_i} \cdot \vec{v_j} \tag{6}$$

Parameter Definitions: Similarity$(\vec{v_i}, \vec{v_j})$ is the dot product of $\vec{v_i}$ and $\vec{v_j}$. $\vec{v_i}$ and $\vec{v_j}$ represent the semantic string vectors of elements i and j after encoding with sentence-bert respectively.

Clustering To classify miRNA-associated and gene-associated diseases into different groups to determine if or how many diseases they associated in common. First, merge the miRNA-associated and gene-associated diseases. The first element of the merged diseases automatically becomes a cluster center. As iterating through the remaining elements, if an element's semantic similarity to the cluster center exceeds the threshold, the element is added to that cluster. Otherwise, it becomes a new cluster center. After clustering, the elements in each cluster are traversed to find the element with the highest similarity sum as the center of the cluster.

$$c^* = \arg\max_{i \in C} \sum_{j \in C, i \neq j} \text{Similarity}(\vec{v_i}, \vec{v_j}) \tag{7}$$

Parameter Definitions: c^* represents the cluster center. C represents the cluster.

Evaluation of Clustering Results The evaluation of clustering results is based on the number of successfully clustered clusters, where a successfully clustered cluster refers to the elements within the cluster that are not a subset of either the miRNA-associated disease or gene-associated disease.

Suppose the number of such clusters is smaller than a value n (in this study, we set n=5), the disease similarity between miRNA and gene is calculated:

$$\text{Similarity matrix}_{ij} = \text{Similarity}(\vec{v_i}, \vec{v_j}) \tag{8}$$

$$\text{Similarity}_{\text{overall mean}} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \text{Similarity matrix}_{ij} \tag{9}$$

Parameter Definitions: m and n denote the number of the miRNA-associated disease and gene-associated disease, respectively.

If the number of successfully clustered clusters exceeds n, the similarity between the two lists is calculated:

$$\text{Similarity matrix}_{pq} = \text{Similarity}(\vec{v_p}, \vec{v_q}) \tag{10}$$

$$\text{Similarity}_{\text{intra-cluster}} = \frac{1}{a \times b} \sum_{p=1}^{a} \sum_{q=1}^{b} \text{Similarity matrix}_{pq} \tag{11}$$

$$\text{Similarity}_{\text{intra-cluster mean}} = \frac{1}{k} \sum_{k=1}^{k} \text{similarity}_{\text{intra-cluster}} \tag{12}$$

Parameter Definitions $\vec{v_p}$ and $\vec{v_q}$ represent the semantic string vectors of the p-th and q-th elements of the successfully clustered cluster, respectively. a and b denote the total number of miRNA-associated diseases and gene-associated diseases in clusters, respectively. k denotes the number of successfully clustered clusters.

Through these steps, we are able to evaluate the disease similarity between the miRNA and gene.

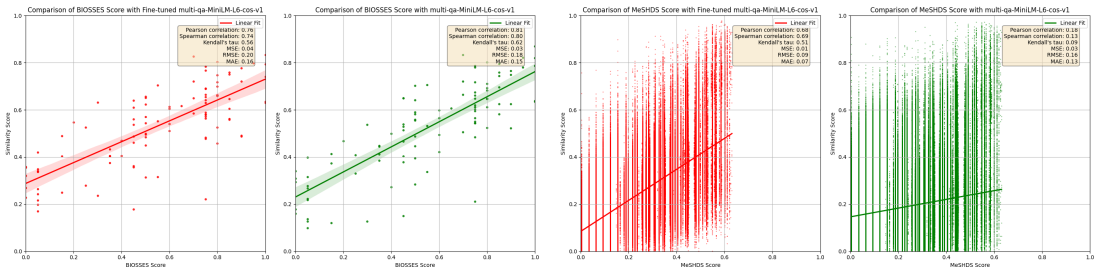
2.3.3 Selection of SBERT Model and Cluster Parameter for the Best Disease Similarity Calculation Performance

The Receiver Operating Characteristic Area Under the Curve (ROC AUC) of a classifier is influenced by different models, clustering parameters, and the choice of classification methods. Therefore, we conducted parameter tuning to identify the optimal model. The test set includes 10 genes that are strongly associated with cancer and have sufficient disease data in DisGeNET, namely TP53, PTEN, KRAS, BCL2, FOXO3, KIF2C, PLK1, CENPA, STAT3 and MYC [24–33]. We hypothesize that a higher degree of similarity indicates a greater likelihood of functional MTIs between miRNA and gene in specific disease. Hence, we employed two linear classification methods, SVM and Logistic Regression, to classify the Functional MTI class and miRWalk class in the test set. We evaluated the ROC AUC of fine-tuned models across various combinations of learning rates and epochs to identify the optimal parameters. Additionally, we explored various clustering thresholds and linear classification methods for each fine-tuned model to identify the threshold and classification method that yields the highest performance.

3 Results

3.1 The Performance of Fine-Tuned SBERT Model for Biomedical Semantic String Analysis

The "MeSHDS" dataset comprises 2,249,975 disease pairs along with their corresponding similarities, a substantial volume of data that ensures the high quality of fine-tuning. To test the performance of the fine-tuned SBERT model, we calculated Pearson's correlation coefficient and Spearman's correlation coefficient between the model output scores and the manually evaluated similarity scores from BIOSSES. Pearson's correlation coefficient reached 0.76 and the Spearman's correlation coefficient reached 0.74 (Figure 4a). We also calculated Pearson's correlation coefficient and Spearman's correlation coefficient between the model output scores and the disease similarity scores from MeSHDS. Pearson's correlation coefficient reached 0.68 and Spearman's correlation coefficient reached 0.69 (Figure 4b). The outcome demonstrates its capacity to preserve the initial pattern while learning new knowledge through fine-tuning.

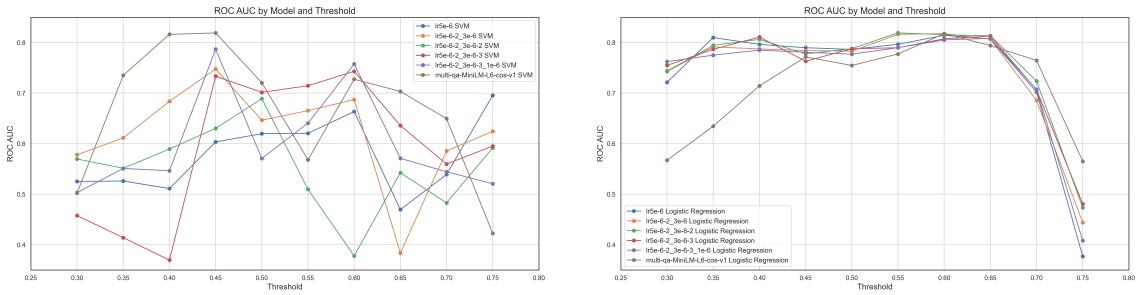


(a) Model Performance in BIOSSES (b) Model Performance in MeSHDS

Figure 4: Comparison of Model Performance

3.2 Model and Cluster Parameter Selection

To achieve the optimal model and parameters, we assessed the classification results through different models and parameter settings. Based on the results of parameter tuning, we discovered that the model achieved optimal performance (ROC AUC=0.82) by undergoing 2 epochs of training on the MeSHDS dataset with a learning rate of "5e-6", followed by an additional 2 epochs with a learning rate of "3e-6" (Figure 5). Subsequently, we selected this particular model and set the cluster threshold to 0.55 before further investigation.



(a) Support Vector Machine (SVM) Classifier (b) Logistic Regression (LR) Classifier

Figure 5: ROC Curves of Different Models and Parameters

3.3 Calculation of Disease Similarity Between miRNAs and Genes throughout Collected MTIs

To obtain disease similarities between MTIs to build a logistic regression classifier. We analyzed 377,312 MTIs from miRTarBase and 156,555,574 MTIs from miRWalk, resulting in a total of 3,900,041 MTIs with disease similarity, including 1,900 miRNAs from HMDD and 7,727 genes from DisGeNET with at least 40 associated diseases. The statistical analysis reveals the distribution of scores (Figure 6, Table 1).

Table 1: Score Summary

Total Count	Mean	Std	Min	25%	50%	75%	Max
3,900,041	0.328	0.165	0.004	0.230	0.259	0.303	0.917

The 'Functional MTIs' from miRTarBase and 'miRWalk' were binary classified based on the score using logistic regression. Since the 'Functional MTI' and the

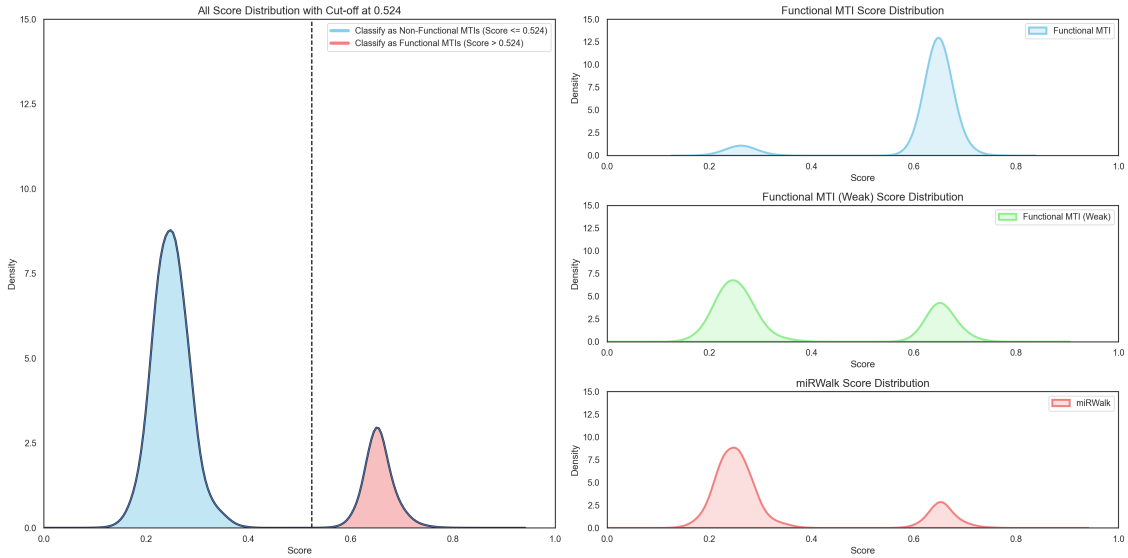


Figure 6: All MTIs, Functional MTIs, Functional MTIs (Weak), and miRWalk Predicted MTIs Score Distributions

'miRWalk' are unbalanced, random sampling was employed for the MTIs with 'miRWalk' label. The model exhibited exceptional classification performance, achieving an ROC AUC of 0.97 during a 20-fold cross-validation (Figure 7), thereby establishing its superiority as a classifier. The decision boundary of the output was determined to be 0.524, indicating that MTIs with scores above this threshold have a high probability of being Functional MTIs in specific diseases. The number of scores that exceed the boundary is 755,707 out of a total of 3,900,041.

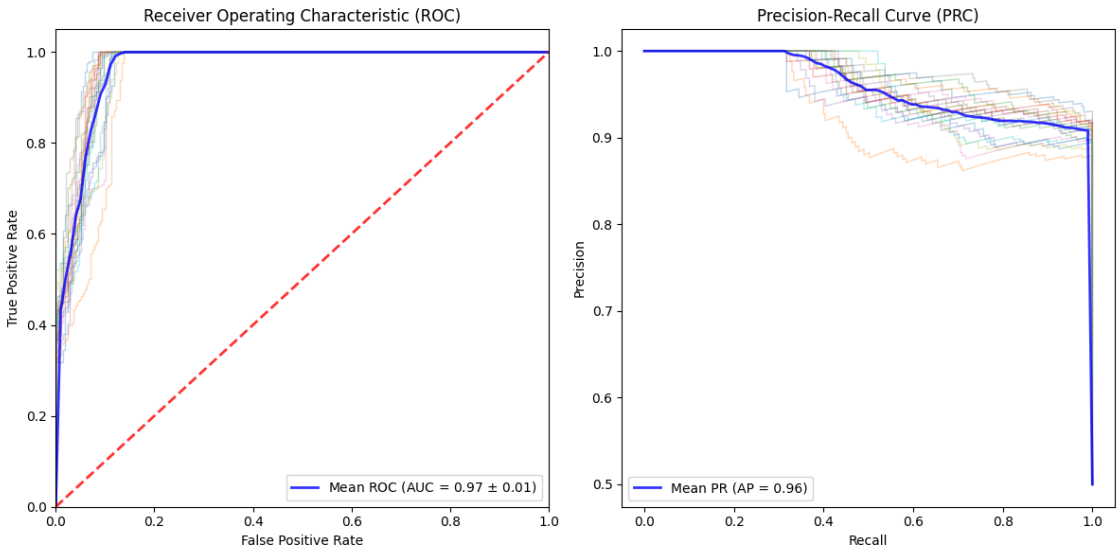


Figure 7: ROC and Precision-Recall Curves of Logistic Regression Classifier

Based on the existing data, we can only calculate the true recall rate of model by selecting MTIs from the intersection of miRTarBase and miRWalk, representing predicted MTIs that have been experimentally verified. The analysis included a total of 226 MTIs. After excluding rows with insufficient miRNA-associated disease (less than 20), a remaining count of 155 Functional MTIs was obtained, and 142 MTIs achieved scores above the threshold (Figure 8), demonstrating a recall rate of 91% (Table 2). This indicates that the model has exhibited reliable performance.

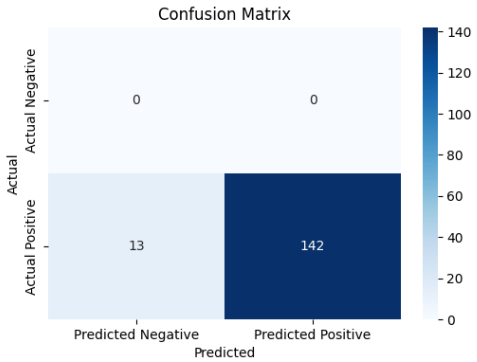


Figure 8: Confusion Matrix of Model Predictions on Intersection MTIs of miRTarBase and miRWalk

Table 2: Model Evaluation Metrics

Metric	Formula	Value
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	0.9161
Precision	$\frac{TP}{TP+FP}$	1.0000
Recall	$\frac{TP}{TP+FN}$	0.9161
F1 Score	$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$	0.9562

TP: True Positives (Correctly Predicted Positives)

TN: True Negatives (Correctly Predicted Negatives)

FP: False Positives (Incorrectly Predicted Positives)

FN: False Negatives (Incorrectly Predicted Negatives)

3.4 Model Generalizability Across Different Databases

The method's generalizability was also assessed by testing its performance on different databases. We manually downloaded the gene-associated disease data from the KEGG database, and within the 10 previously mentioned genes associated with cancer, only TP53, PTEN, KRAS, and MYC have enough gene-associated diseases in KEGG. These genes were selected for generating 2994 MTIs' disease similarity with both DisGeNET database and KEGG database. The correlation coefficient between these two databases were calculated. Pearson's correlation coefficient exceeds 0.8 and Spearman's correlation coefficient approximate 0.8 (Figure 9). This result serves as evidence that the method exhibits generalizability across different databases.

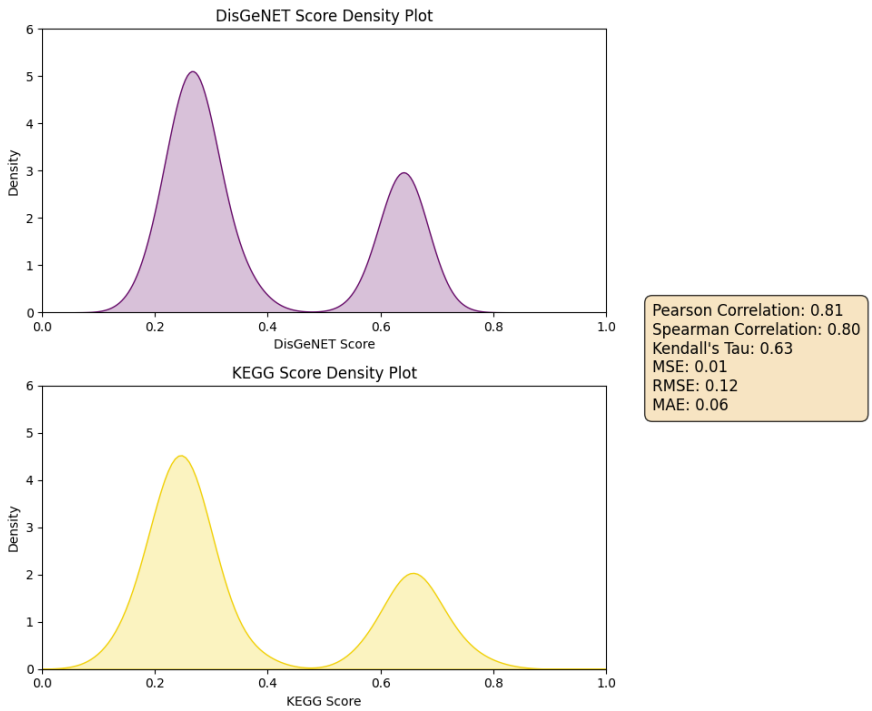
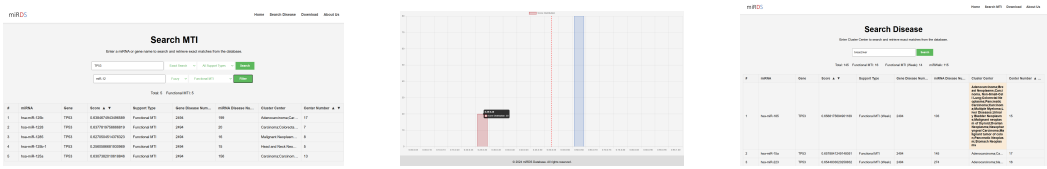


Figure 9: Peak Plot of Score Calculated Using the DisGeNET Database and KEGG Database

3.5 miRNA Disease Similarity (miRDS) Website Construction

To visualize the results of calculations, we developed the miRDS website (Figure 10), which enables users to search for MTIs and obtain corresponding disease similarity scores. Additionally, specific diseases can be searched to identify functional MTIs associated with them. The website also offers the flexibility to sort the output in ascending or descending order, along with a histogram displaying the score distribution of the search results at the bottom of each page. The MTIs located to the right of the dotted line are regarded as potential candidates with a higher disease similarity between miRNA and gene. We recommend selecting MTIs with a minimum of 20 miRNA-associated diseases to enhance the credibility of predictions.



(a) Search MTIs (b) Score Histogram of MTIs Search (c) Search Functional MTIs in Diseases

Figure 10: miRDS Database Website

4 Discussion

The present study proposes a method to further refine the selection of MTIs from sequence-based prediction tools by incorporating disease similarity analysis between miRNAs and genes, ultimately leading to the establishment of a prediction database for disease-specific MTIs. The distribution of three different types of similarity scores indicates that the density of high scores (greater than 0.524) is generally highest in Functional MTIs, followed by Functional MTIs (Weak), and lowest in miRWalk. These findings support our hypothesis that higher scores indicate a greater likelihood of functional MTIs. The reason may attributed to the fact that a majority of experimentally validated human MTIs possess specific biological implications, such as playing a significant role in disease pathogenesis. The method demonstrates a strong correlation between MTIs and diseases, as the computation of disease semantic similarity between miRNA and Gene can greatly predict the type of MTIs.

Moreover, considering the abundance of miRNA-associated disease and gene-associated disease data, our proposed method holds great potential for widespread application. Notably, the DisGeNET database encompasses 21,671 genes linked to various disease types, while HMDD provides information on 1,900 miRNAs and their associated diseases. The estimated total number of human genes is approximately 22,333 [34], while the estimated number of mature miRNAs in humans is around 2,300 [35]. Based on estimation, the method has the capability to encompass a substantial proportion of both miRNAs and genes. More importantly, compared to previous disease similarity algorithms, such as the MISIM and SemFunSim [36, 37], the SBERT-based disease similarity computation method does not require the input that the disease must be present on the MeSH Tree, which greatly improves the scope of the computation.

However, there are still limitations. Despite the extensive coverage of miRNAs and genes in the current database, the number of diseases associated with a single miRNA and gene remains limited. In the case of DisGeNET, when I screened genes with over 40 diseases, the gene count decreased from over 20,000 to around 8000. The lack of sufficient disease data can undermine the accuracy of classification and weaken the persuasiveness of the results. Additionally, insufficient computational resources hindered the analysis as only the top 40 gene-associated diseases were considered for analysis. As the number of gene-associated diseases increases, it significantly prolongs the running time of the model, posing difficulties in handling large-scale data calculation.

5 Perspective

The results of the experiment and the model's performance on BIOSSES and MeSHDS datasets demonstrate that the Natural Language Processing (NLP) method excels in calculating semantic string similarity in biomedical contexts after specific fine-tuning. The method demonstrates promising scalability and can also be applied to compute the disease semantic similarity or functional semantic similarity between other biomolecules, thereby facilitating the exploration of their interactions. In addition to predicting interactions based on physical and chemical properties, the method provides novel insights into disease semantic similarity and functional semantic similarity, thereby optimizing the analysis.

Regarding application prospects, we propose a scenario where performing miRNA profiling on diseased tissue samples from clinical patients allows obtaining a substantial amount of miRNA-associated disease data. A similar approach can also be employed to acquire gene expression data to enhance the identification of gene-associated diseases. By utilizing this approach, it may become feasible to construct an comprehensive MTIs network in diseases, providing robust support for future diagnosis and treatment [38].

Declarations

Equipment

The computations were performed using an NVIDIA A100 GPU with 80GB of memory.

Funding

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Availability of data and materials

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. The MeSHDS dataset can be gained through 'Baiming123/MeSHDS' in HuggingFace. The miRDS database will be available soon.

Patent

A patent application related to the work presented in this paper has been filed Patent Application No.202410559682.3 Title: 基于文本的MicroRNA和基因关系挖掘方法、装置、设备及介质. For patent licensing or commercial application, contact: baimingchen@link.cuhk.edu.cn.

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