Hierarchical MixUp Multi-label Classification with Imbalanced Interdisciplinary Research Proposals

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Abstract

Funding agencies are largely relied on a topic matching between domain experts and research proposals to assign proposal reviewers. As proposals are increasingly interdisciplinary, it is challenging to profile the interdisciplinary nature of a proposal, and, thereafter, find expert reviewers with an appropriate set of expertise. An essential step in solving this challenge is to accurately model and classify the interdisciplinary labels of a proposal. Existing methodological and application-related literature, such as textual classification and proposal classification, are insufficient in jointly addressing the three key unique issues introduced by interdisciplinary proposal data: 1) the hierarchical structure of discipline labels of a proposal from coarse-grain to fine-grain, e.g., from information science to AI to fundamentals of AI. 2) the heterogeneous semantics of various main textual parts that play different roles in a proposal; 3) the number of proposals is imbalanced between non-interdisciplinary and interdisciplinary research. Can we simultaneously address the three issues in understanding the proposal’s interdisciplinary nature? In response to this question, we propose a hierarchical mixup multiple-label classification framework, which we called H-MixUp. H-MixUp leverages
2 \textit{H-Mixup}

A transformer-based semantic information extractor and a GCN-based interdisciplinary knowledge extractor for the first and second issues. H-MixUp develops a fused training method of Wold-level MixUp, Word-level CutMix, Manifold MixUp, and Document-level MixUp to address the third issue. Finally, the experiments show that H-MixUp can improve the SOTA performance by 14\% on the imbalanced dataset when categorizing interdisciplinary data. Other experimental results demonstrate that H-MixUp can alleviate the overfitting from the training step and help the model learn balanced attention from the semantic information.

\textbf{Keywords:} Imbalanced Learning, MixUp, Hierarchical Multi-label Classification

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig1.png}
\caption{An example of the proposal and its related multiple discipline labels on discipline structure.}
\end{figure}

1 \textbf{Introduction}

In most funding agencies, the major grant awarding mechanism is to score proposals based on their intellectual, educational, and socio-societal merits. In this process, proposals are submitted to open-court competitive programs managed by government agencies. Proposals are then assigned to appropriate reviewers to solicit review comments and ratings. One of the pains of running such a peer-review system is to assign a proposal to a set of appropriate domain reviewers to advance the effectiveness and fairness of the review process. With the increasingly growing number of research proposals over years, it is appealing to introduce artificial intelligence (AI) to assist this process.

We define the task of classifying a proposal into its correlated domains as Interdisciplinary Research Proposal Classification (IRPC), which aims to
assign a proposal to one or more label paths that follow a hierarchical discipline structure. For example, figure 1 illustrates an example of the research proposal and its related multiple discipline labels in the hierarchical discipline structure. Figure 1(1) is a research proposal dataset, where each square represents a research proposal. The color of a square shows its disciplines. We use a single color square to represent a non-interdisciplinary research (NIR) proposal, and use a multi-color square to represent an interdisciplinary research (IR) proposal. In the National Natural Science Foundation of China (NSFC), thousands of disciplines and sub-disciplines are organized into a hierarchical structure to better index, search, and match reviewers and proposals. Each discipline is associated with a unique alphabetical identifier, which is called ApplyID. The ApplyID system can be viewed as a Directed Acyclic Graph (DAG) or a tree. Every ApplyID code is prefixed by a capital letter from A to H, representing a discipline or a sub-discipline, followed by digits ranging from zero to six. Every two-digit number in the ApplyID code represents a sub-discipline division in a particular granularity. Figure 1(2) illustrates an example of ApplyID of a proposal: F refers to the major discipline Information Sciences. F06 represents Artificial Intelligence, a sub-discipline of Information Sciences, and F0601 represents Fundamentals of Artificial Intelligence, a sub-discipline of F06. The red shading represents the target discipline label. The C (Life Sciences) and its sub-discipline C09 (Neuroscience and Psychology) are another discipline path of the proposal.

Many impactful research problems require interdisciplinary solutions that combine the scientific discoveries and inventions across different domains. Therefore, the growth of interdisciplinary research can dramatically enhance the evolution of the sciences. However, in the current research fund application, the IR remains a small part of the whole grant system. For example, out of 280,683 research proposals submitted to NSFC in 2020, only 20,631 proposals (i.e., 7%) are marked with two major disciplines. This imbalanced data introduce bias into model training in proposal classification. This phenomenon will affect the performance and make the model insensitive to the IR.

\footnote{\url{http://www.nsfc.gov.cn/publish/portal0/tab550/}}
proposal classification. Figure 2 illustrates the impact of imbalance on model training. On the one hand, the proportion of blue shade (i.e., total correct) in Figure 2(1) shows that classification models can categorize the NIR research, which only contains one label path, into a correct label path precisely. On the other hand, the green shade (i.e., half correct) in Figure 2(2) holds a majority share, showing that classification models tend to classify the IR data, which contains two label paths, into only one correct label path. This analysis shows that the proportion of IR data and NIR data in the training set significantly impact the classification performance on these two kinds of data. To sum up, instead of the imbalanced data number in each class, the problem in IRPC task behaves as unevenness of label number in each case.

Inspired by the MixUp [8] and its application in imbalanced learning [9, 10] with a particular dataset, we apply the MixUp and its variant methods to the IRPC task and propose a novel training strategy called the H-MixUp. The H-MixUp strategy focuses on solving the label number imbalance in the HMC schema tasks, e.g., the IRPC task. The main difference between H-MixUp and other MixUp methods is that it mixes the input features and the previous prediction results or hidden state among each prediction step simultaneously. In conclusion, our contributions are as follows:

(1) We study an interesting AI-assisted proposal classification problem. The proposal data exhibit three fundamental complexities: hierarchical discipline structure, heterogeneous textual semantics, and data label imbalance.

(2) We generalize this proposal classification problem into a hierarchical multi-label path classification task. We propose a novel framework H-MixUp that enables the integration of transformer-based textual semantics modeling and interdisciplinary knowledge learning and alleviates the data imbalance.

(3) We conduct extensive experiments to evaluate the performance of various H-MixUp strategies. In particular, the Word-level MixUp strategy can balance the attention between each keyword from different domains and achieve the best performance compared to other MixUp strategies.

2 Definitions and Problem Statement

2.1 Data Definitions

2.1.1 Research Proposal

Applicants write proposals to apply for grants. Figure 1(2) show a proposal includes multiple documents such as Title, Abstract, and Keywords, Research Fields, and more. Let’s denote a proposal by $A$, the documents in a proposal are denoted by $D = \{d_i\}_{i=1}^{T}$ and the types of each document are denoted by $T = \{t_i\}_{i=1}^{T}$. The $|T|$ is the total number of the document types, and $d_i$ is the document of $i$-th type $t_i$. Every document $d_i$ in the proposal, denoted as $d_i = [w_i^1, w_i^2, ..., w_i^{d_i}]$, is a sequence of words, where $w_i^k$ is the $k$-th word in the document $d_i$. 
2.1.2 Hierarchical Discipline Structure

A hierarchical discipline structure, denoted by $\gamma$, is a DAG or a tree that is composed of discipline entities and the directed Belong-to relation from a discipline to its sub-disciplines. The discipline node set $C = \{C_0 \cup C_1 \cup \ldots \cup C_H\}$ are organized in $H$ hierarchical levels, where $H$ is the depth of hierarchical levels, $C_k = \{C_{k1} \mid i = 1\}$ is the set of the disciplines in the $i$-th level. $C_0 = \{\text{root}\}$ is the root level of $\gamma$. To describe the connection between different disciplines, we introduce $\prec$, a partial order representing the Belong-to relationship. $\prec$ is asymmetric, anti-reflexive and transitive [11]:

- The only one greatest category root is the root of the $\gamma$,
- $\forall c_i^x \in C_i, c_j^y \in C_j, c_i^x \prec c_j^y \rightarrow c_i^x \neq c_j^y$,
- $\forall c_i^x \in C_i, c_i^x \neq c_i^x$,
- $\forall c_i^x \in C_i, c_j^y \in C_j, c_k^z \in C_k, c_i^x \prec c_j^y \wedge c_j^y \prec c_k^z \rightarrow c_i^x \prec c_k^z$.

Finally, we define the Hierarchical Discipline Structure $\gamma$ as a partial order set $\gamma = (C, \prec)$.

2.1.3 Topic Path

In this paper, we define the target labels of each research proposal as the topic path $L = [L_0, L_1, L_2, \ldots, L_H]$, $L_i = \{l_i^j\}_{j=1}^{L_i}$ is a set of the labels in the label paths on the $i$-th level (i.e., $\forall l_i^j \in L_i \rightarrow l_i^j \in C_i$). $H_A$ is the proper length of label paths. For example, in the Figure 1, the input research proposal are labeled by the ApplyID codes F0601 and C09. So the $L$ for this research proposal can be processed as $[\{l_{\text{root}}\}, \{F, C\}, \{F06, C09\}, \{F0601, l_{\text{stop}}\}]$. The $l_{\text{root}}$ stands for the root node of the discipline structure. The $l_{\text{stop}}$ is a stop token, which is appended to the last set in $L$ to denote the topic path ended.

2.1.4 Interdisciplinary Graph

A discipline is a combination of domain knowledge and topics. On the one hand, those topics will be carefully selected [12] by the applicants to represent the key idea of their research proposal. On the other hand, the overlapping topic (co-topic) between disciplines could represent their similarity. So, how to measure interdisciplinarity? S. W. Aboelela [13] believes that interdisciplinary research is engaging from two seemingly unrelated fields, which means: (1) these disciplines will have few overlapped topics. (2) those overlapped topics will be frequently cited by the researchers. In this paper, we adopt the Rao-Stirling [14] (RS) to measure interdisciplinarity. The RS is a non-parametric quantitative heuristic, which is widely adopted to measure the diversity in science [14–16], the ecosystem [17] and energy security [18]. The RS is defined as:

$$RS = \sum_{ab(a \neq b)} (p_a \cdot p_b)^\alpha \cdot (d_{ab})^\beta,$$  \hspace{1cm} (1)
where the first part $\sum_{ab(a\neq b)}(p_a \cdot p_b)$ are proportional representations of elements $a$ and $b$ in the system, and the rest $\sum_{ab(a\neq b)}d_{a,b}$ is the degree of difference attributed to elements $a$ and $b$. The $\alpha$ and $\beta$ are two constant to weighting the two components. We introduce the RS in a micro view to define the weight on $e_{a\rightarrow b}$:

$$e_{a\rightarrow b} = (p_{a\rightarrow b})^\alpha (d_{a\rightarrow b})^\beta,$$

where $p_{a\rightarrow b}$ is the proportion of the proposals in discipline $a$ that contain same topics in $b$, which represents the co-selected frequency of $a$ to $b$. $d_{a\rightarrow b}$ is the proportion of topic overlap from $a$ to $b$. Their detailed definitions are as:

$$p_{a\rightarrow b} = \frac{\sum_{i} \mathbb{1}(k_i \in \{K_a \cap K_b\}) F_a[k_i]}{\sum_{i} F_a[k_i]},$$

$$d_{a\rightarrow b} = 1 - \frac{|K_a \cap K_b|}{|K_a|},$$

where the $\mathbb{1}(\cdot) \rightarrow \{0, 1\}$ is the indicator function, $K_a$ and $K_b$ are topic set of $a$ and $b$, $n$ is the total number of the topic. $F_a$ and $F_b$ are two lookup table holding the frequency of each topic being selected in the proposals that relat to $a$ and $b$.

By that, we build a Interdisciplinary Graph, denoted as $G = (C, E)$, to represent the interdisciplinarity among disciplines. $G$ is a collection of discipline set $C$ and directed weighted edge set $E = \{e_{a\rightarrow b}\}_{a,b=1}^{C}$. Each $e_{a\rightarrow b} \geq 0$ represents the interdisciplinary strength from discipline $a$ to discipline $b$.

2.2 Problem Formulation

We formulate the IRPC task in a hierarchical classification schema and use a sequence of discipline-level-specific label sets $L$ as topic path to represent the proposals’ disciplinary codes. Given the proposal’s document set $D$ and interdisciplinary graph $G$, we decompose the prediction process into an top-down fashion from the beginning level to a certain level on the hierarchical discipline structure $\gamma$. Suppose the $k - 1$ ancestor labels in $L$ are $L_{<k} = [L_0, L_1, ..., L_{k-1}]$, where $L_{<1} = \{L_0\}$, the prediction on level $k$ can be seem as a multi-label classification on level-$k$, formulated as:

$$\Omega(D, G, L_{<k}, \gamma; \Theta) \rightarrow L_k$$

where $\Theta$ is the parameters of model $\Omega$. Eventually, we can formulate the probability of the assignment of the sequence of label sets for the proposal in prediction as:

$$P(L|D, G, \gamma; \Theta) = \prod_{k=1}^{H_A} P(L_k|D, G, L_{<k}, \gamma; \Theta)$$
where $L_k \subset L$ is the level-$k$ target label set. $P(L|D,G,\gamma; \Theta)$ is the overall probability of the proposal $A$ belonging to the label set sequence $L$, $P(L_k|D,G,\gamma, L_{<k}; \Theta)$ is the label set assignment probability of $A$ in level-$k$ when given the previous ancestor $L_{<k}$. In training, given all the ground truth labels, our goal is to maximize the probability in Equation 5.

### 2.3 MixUp Definition

The MixUp is a regularization technique for improving the model generalization. Most of the MixUp methods behave as a data pre-processing or a data augmentation for creating the pseudo features and the pseudo labels, so that an Empirical Risk Minimization [19] task can be converted to a Vicinal Risk Minimization [20] task. We give a formal definition of MixUp methods as follows:

$$\tilde{x} = f_x(x_a, x_b), \quad \tilde{y} = f_y(y_a, y_b),$$

where $(x_a, y_a)$ and $(x_b, y_b)$ are two samples drawn at random from the training data. The $x_a, x_b \in \mathbb{R}^{n \times h}$ are the features of input data, where $n$ is the total length of input text sequence and $h$ is the hidden size of input feature, and the $y_a$ and $y_b$ are their corresponding one-hot labels. The $f_x(\cdot)$ and $f_y(\cdot)$ are two mixup functions. The $\tilde{x}$ and $\tilde{y}$ are the mixed feature and mixed label, respectively.

In the original MixUp method [8], those mixing processes of feature pair and label pair are done by using a mixing factor $\lambda$ which is sampled from a beta distribution with a hyperparameter $\alpha$:

$$f^m_x(x_a, x_b) = \lambda x_a + (1 - \lambda)x_b, \quad f^m_y(y_a, y_b) = \lambda y_a + (1 - \lambda)y_b, \quad \text{where } \lambda \sim \text{Beta}(\alpha, \alpha),$$

where the $f^m_x(\cdot)$ and $f^m_y(\cdot)$ are the original MixUp functions for features and labels.

There is another approach named CutMix [21] which is inspired by MixUp and CutOut [22]. The original CutMix cut two input images with a sampled width and height then spliced them to form mixed training data. In our IRPC task, we first sampled the $\gamma$ from the beta distribution. Then, the model initializes the cut position and cut length for constructs a 1-d mask vector $m \in \mathbb{R}^{1 \times n}$. After that, we use $m$ and $\gamma$ to form the input mixed data:

$$f^c_x(x_a, x_b) = m \odot x_a + (1 - m) \odot x_b, \quad f^c_y(y_a, y_b) = \lambda y_a + (1 - \lambda) y_b, \quad \text{where } m \sim f(\cdot|\text{start}, \text{dur}), \quad \text{and } \lambda \sim \text{Beta}(\alpha, \alpha),$$

$^2$In this paper, we use $\tilde{\cdot}$ to mark a mixed feature, a mixed label, or a modified function with MixUp.
where the $\odot$ is a element-wise multiplication. $f_x^c(\cdot)$ is the feature mixup function in CutMix method. The mask vector $m$ is generated by the mapping function $f(\cdot)$ that involves the cut position $\text{start}$ and the cut length $\text{dur}$, where the elements from $m[\text{start}]$ to $m[\text{start} + \text{dur}]$ are zero, and the rest positions are one. The $\text{start}$ index is randomly sampled from a uniform distribution $\text{start} \sim \text{Uniform}(0, n)$, and the cut length $\text{dur}$ is generated by the $\text{dur} = \text{int}(\lambda \ast n)$.

### 3 Methodology

#### 3.1 Model Overview

We start this section by giving an overview of Hierarchical Interdisciplinary Research Proposal Classification Network (HIRPCN) [23] and H-MixUp. The left part of Figure 3 shows the iteration process of HIRPCN. In each level’s prediction, the input of HIRPCN consists of two parts: the multiple types of text data $D$ and the prediction results $L_{<k}$ from the previous $k-1$ steps. There are three major components in HIRPCN: (1) **Semantic Information Extractor** (SIE) models the semantic components in research proposals according to their particular type (e.g., title, abstract, keywords, research fields) and encodes them into a matrix. (2) **Interdisciplinary Knowledge Extractor** (IKE) obtains the representation of previous prediction results from the pre-built interdisciplinary graphs. (3) **Information Fusion** (IF) fuses the type-specific semantic information and the representation of previous prediction results. After information fusion, the model feeds the fused information into a level-wise prediction and forms the probability of the current-level discipline labels. Based on this pipeline, We incorporate the H-MixUp for feature extracting and model training. As the right part of Figure 3 illustrated, given the document set $D^a \in A^a$, $D^b \in A^b$ with their corresponding previous prediction results $L^a_{<k}$ and $L^b_{<k}$, the H-MixUp is integrated into the SIE and the IKE to separately mix the semantic information and the previous prediction results.
The rest of this section is listed as follows: In Section 3.2, we introduce the SIE component and four strategies to mix the semantic feature from the research proposal. In Section 3.3, we present the IKE and how to mix and incorporate the previous prediction results. In Section 3.4, we introduce how we fuse the mixed feature. In Section 3.5 we present the model training and give a formal definition of the loss function in H-MixUp.

### 3.2 H-MixUp with the Semantic Information

#### 3.2.1 Semantic Information Extractor

An illustration of SIE is shown in Figure 4(1). The SIE consists of a hierarchical Transformer\(^3\) structure. We design two components for SIE: 

**Word-level Transformer** is the building-block of SIE to extract the semantic information within the input text sequence:

\[
W_i^{(l)} = \text{Transformer}_w(W_i^{(l-1)}),
\]

where the \(\text{Transformer}_w(\cdot)\) is a multi-layer word Transformer. The \(W_i^{(l)} \in \mathbb{R}^{n \times h}\) is the intermediate state of the type \(i\) document representation matrix in layer-(\(l\)) of the Word-level Transformer.

**Document-level Transformer** aims to utilize the type of document (e.g., the title, the abstract, etc.) to model the importance of the input and generate the type-specific representation of the research proposal:

\[
D^{(l)} = \text{Transformer}_d(\{d_i^{(l-1)} \odot W_i^{(l)}\}_{i=1}^{|T|}),
\]

\(^3\)The detailed explanation of the Transformer can be found in [24].
where the Transformer\(_d(\cdot)\) is a multi-layer document Transformer. \(d_i^{(l-1)} \in \mathbb{R}^h\) is the type embedding of documents in type \(i\) from the previous layers of Document-level Transformer output or from a random initialized vector in the first layer input of the Document-level Transformer. The \(\odot\) is a fusing operation. Inspired by ViT\([25]\) and TNT\([26]\), we set the \(\odot\) operation as: (1) a Vectorization Operation on \(W_i^{(l)}\). (2) a Fully-connected Layer to transform the vanilla document representation from dimension \(nh\) to dimension \(h\). (3) an Element-wise Add with the vector.

We set the total layer number of the Transformer in SIE to \(N_e\). After propagating the contextualized semantic information and type information for \(N_e\) times, the SIE finally outputs the type-specific document representation: \(D = D^{(N_e)}\). To sum up, given the input documents set \(D\), we can formulate the dataflow in SIE as:

\[
D = \text{SIE}(D),
\]

(11)

### 3.2.2 H-MixUp for Semantic Information

We deploy the H-MixUp for semantic information in three positions: 1) the word embedding input before the Word-level Transformer, 2) the word embedding input in an arbitrary layer of the Word-level Transformer, 3) the document representation input of the Document-level Transformer. The rest of this section introduces four H-MixUp strategies for the research proposal in those positions:

**Word-level MixUp:** The first strategy is using MixUp before the input of the Word-level Transformer. As Figure 4(2)(a) shows, given two type-\(i\) text features \(W^a_i\) and \(W^b_i\) from \(D_a\) and \(D_b\), respectively, we form the mixed feature using the MixUp function \(f^m(\cdot)\) the Equation 7:

\[
\tilde{W}_i = f^m(W^a_i, W^b_i).
\]

(12)

After that, we feed the \(\tilde{W}_i\) into the Word-level Transformer and the Document-level Transformer.

**Word-level CutMix:** The second strategy is using CutMix instead of MixUp before the input of the Word-level Transformer. As Figure 4(2)(b) shows, given two type-\(i\) text features \(W^a_i\) and \(W^b_i\) from \(D_a\) and \(D_b\), respectively, we obtain the mixed feature with the MixUp function \(f^c(\cdot)\) in the Equation 8:

\[
\tilde{W}_i = f^c(W^a_i, W^b_i).
\]

(13)

After that, we feed the mixed feature into the Word-level Transformer and the Document-level Transformer.

**Manifold MixUp:** The third strategy is using MixUp in a random layer of SIE. As Figure 4(2)(c) illustrates, we randomly select a layer-\(l\) in each minibatch, and form the mixed feature. Given two document set \(D_a\) and \(D_b\), we can obtain the type-\(i\) document representation matrix \(W^{a(l)}_i\) and \(W^{b(l)}_i\)
from the output of the layer-\(l\)’s Word-level Transformer:

\[
\hat{\mathbf{W}}_i^{(l)} = f^m_x(\mathbf{W}_i^{a(l)}, \mathbf{W}_i^{b(l)}).
\] (14)

Then the mixed feature \(\hat{\mathbf{W}}_i^{(l)}\) is fed into the Document-level Transformer and the next levels of the Word-level Transformer.

**Document-level MixUp:** The last strategy is to MixUp the document representations. As Figure 4(2)(d) shows, given two document set \(D_a\) and \(D_b\), suppose the current layer number is \(l\), we can obtain the type-\(i\) document representation matrix \(\mathbf{W}_i^{a(l)}\) and \(\mathbf{W}_i^{b(l)}\) from the output of the Word-level Transformer. Then we form the mixed type-\(i\) document feature by the Equation 7:

\[
\{\hat{\mathbf{W}}_i^{(l)}\}_{l=0}^{N_e} = \{f^m_x(\mathbf{W}_i^{a(l)}, \mathbf{W}_i^{b(l)})\}_{l=0}^{N_e}.
\] (15)

In every layer of SIE, we mix the feature after the Word-level Transformer and feed the mixed document feature into the Document-level Transformer.

After \(N_e\) iterations, we finally obtain the mixed type-specific semantic feature \(\tilde{\mathbf{D}}\) of the research proposal. The process of the Equation 11 is modified to:

\[
\tilde{\mathbf{D}} = \tilde{\text{SIE}}(D^a, D^b),
\] (16)

where \(\tilde{\text{SIE}}(\cdot)\) is the SIE(\cdot) module with H-MixUp strategy.

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**Fig. 5** Mix the step-\(m\) prediction result from sample \(a\) and sample \(b\).
3.3 H-MixUp with the Previous Predictions

3.3.1 Interdisciplinary Knowledge Extractor

The IKE is a Graph Convolutional Network\(^4\) (GCN) based component that aims to embed the previous prediction results and their correlated interdisciplinary knowledge. In particular, the progress of IKE in step-\(k\) could be divided into two parts:

First, we use each set of results in the sequence \(L_{<k}\) as the central nodes to sample their neighborhoods from the pre-built interdisciplinary graph \(G\). Then, each sampled sub-graph is fed into \(N_g\) layer of GCNs to aggregate the interdisciplinary knowledge feature. For example, the prediction results in level \(m\) \((m < k)\) can be processed as:

\[
H_m = GCNs(g_m, H_m^{(0)}),
\]  

(17)

where the \(H_m^{(0)}\) is the initial representation of the input node in step \(m\). \(g_m\) denoted the sampled sub-graph.

Second, we generate the representation of predicted set by a ReadOut operation from the aggregated feature.

\[
e_m = \text{Readout}(H_m, L_m),
\]  

(18)

where the \(\text{Readout}\) is a lookup operation (i.e., take the \(L_m\) included node embedding) followed by a mean pooling layer. The \(e_m \in \mathbb{R}^h\) is the final representation of \(L_m\). Based on that, with the given previous \(k-1\) step prediction result sequence \(L_{<k}\), we can obtain their representations \(E_{<k}\) by:

\[
E_{<k} = IKE(L_{<k}),
\]  

(19)

3.3.2 H-MixUp for Previous Predictions

In H-MixUp, the essential idea is to mix the previous predicted result in each step of prediction. As Figure 5 illustrated, given the level \(m\) prediction result set \(L_m^a \in L_{<k}^a\) and \(L_m^b \in L_{<k}^b\), we first sample their subgraphs and \(\text{ReadOut}\) the representation \(e_m^a\) and \(e_m^b\). Then, we mix the feature of previous prediction by the same \(\lambda\) we introduce in the Equations 7 and 8:

\[
\tilde{e}_m = \lambda e_m^a + (1 - \lambda)e_m^b,
\]  

(20)

where the \(\tilde{e}_m\) is the mixed feature of level-\(m\) prediction. Thus, we can obtain the previous \(k\) level mixed embedding set \(\tilde{E}_{<k} = \{\tilde{e}_m\}_{m=0}^{(k-1)}\) by:

\[
\tilde{E}_{<k} = IKE(L_{<k}^a, L_{<k}^b),
\]  

(21)

where \(IKE(\cdot)\) is the IKE(\cdot) in the Equation 19 with the H-MixUp strategy.

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\(^4\)The detailed explanation of the Graph Convolutional Network can be found in [27]
### 3.4 Information Fusion

The Information Fusion (IF) is a multi-layer component built to combine the previously mixed semantic information and interdisciplinary knowledge. We first sum the mixed feature $\tilde{E}_{<k}$ with positional encoding for preserving the order of predictions. Then, we perform Multi-Head Self-Attention between each prediction result representation to help each element from the previous layer aggregate knowledge from their context. The process in layer $l$ is defined as:

$$\hat{S}^{(l)}_{<k} = \hat{S}^{(l-1)}_{<k} \circ \text{MultiHead}(\tilde{E}_{<k}, \tilde{E}_{<k}, \tilde{E}_{<k})),$$

where $\circ$ operation is a Layer Normalization with a Residual Connection Layer. In this step, the $\text{MultiHead}(\cdot)$ adaptively aggregate the context information from every step prediction, and the $\circ$ operation integrate the context knowledge to the prediction result embedding and form the the level-$l$ prediction state as $\hat{S}^{(l)}_{<k} \in \mathbb{R}^{k \times h}$.

Secondly, we treat the prediction state $\hat{S}^{(l)}_{<k}$ as Query and the mixed feature of document set $\tilde{D}$ as Key and Value into another Multi-head Attention to propagate the semantic information:

$$\begin{align*}
Z^{(l)} &= \hat{S}^{(l)}_{<k} \circ \text{MultiHead}(\hat{S}^{(l)}_{<k}, \tilde{D}, \tilde{D})), \\
\tilde{S}^{(l)}_{k} &= Z^{(l)} \circ FC(Z^{(l)}),
\end{align*}$$

The $\text{MultiHead}(\cdot)$ adaptively aggregate the semantic information from the research proposal by the current prediction state, and the $\circ$ operation integrate the semantic information to the label embedding and construct the hidden feature $Z^{(l)}$ in level-$l$. After a Fully-connected Layer denoted as $FC(\cdot)$ and the $\circ$ operation, we form $\tilde{S}^{(l)}_{k}$ to hold the fusion information in layer $l$.

After $N_d$ times propagations, we acquire the $\tilde{S}_{k} = \tilde{S}^{(N_d)}_{k}$ to represent the output of IF. The information fusion in step $k$ can be formulated as:

$$\tilde{S}_{k} = \text{IF}(\tilde{D}, \tilde{E}_{<k}),$$

### 3.5 Training Strategy of H-MixUp

From the previous section, we obtained the fusion information $\tilde{S}_{k}$. For a level-wise prediction, we feed the fused feature matrix $\tilde{S}_{k}$ into a Pooling Layer, a Fully-connected Layer, and a Sigmoid Layer to generate each label’s probability for $k$-th level-wise label prediction. In our paper, we set this Pooling Layer as directly taking the last vector of $\tilde{S}_{k}$. The formal definition is:

$$\tilde{y}_k = \text{Sigmoid}(FC_k(\text{Pooling}(\tilde{S}_{k}))),$$

where the $\tilde{y}_k$ is the probability (i.e., $P(L_k | D, G, \gamma, L_{<k}; \Theta)$ in Equation 5) for each discipline in $k$-th level of hierarchical discipline structure $\gamma$. It is worth
noting that we add a $l_{\text{stop}}$ token in each step to determine the prediction state. Thus, the $F_{C_k}(\cdot)$ denotes a level-specific feed-forward network with a ReLU activation function to project the input to a $|C_k| + 1$ length vector, where represents the label number of level-$k$ with $l_{\text{stop}}$ token. After the $\text{Sigmoid}(\cdot)$, the final output $\tilde{y}_k$ is the probability of $k$-th level’s labels.

For step-$k$ of training progress, given the selected pair $A^a$ and $A^b$, the level-wise loss function is defined as:

$$\tilde{L}_k(\Theta) = \sum_{i=1}^{|C_k|+1} \left( \tilde{Y}_k(i) \log(\tilde{y}_k^i) + (1 - \tilde{Y}_k(i)) \log(1 - \tilde{y}_k^i) \right),$$

(26)

$$\tilde{Y}_k(i) = \begin{cases} 
0 : l_i \notin L^a_k \cup L^b_k \\
\lambda : l_i \in L^a_k, l_i \notin L^b_k \\
1 - \lambda : l_i \in L^b_k, l_i \notin L^a_k \\
1 : l_i \in L^a_k \cap L^b_k
\end{cases},$$

where the $\tilde{y}_k^i$ is the $i$-th label’s probability after the H-MixUp. Thus, the overall loss function $\tilde{L}(\Theta)$ is formulated as:

$$\tilde{L}(\Theta) = \sum \tilde{L}_k(\Theta).$$

(27)

During the training process with H-MixUp, our target is to optimize the objective function $\tilde{L}(\Theta)$.

| Prefix | Major Discipline Name | Total | $|C_2|$ | $|C_3|$ | $|C_4|$ |
|--------|-----------------------|-------|--------|--------|--------|
| A      | Mathematical Sciences | 318   | 6      | 57     | 255    |
| B      | Chemical Sciences     | 392   | 8      | 59     | 325    |
| C      | Life Sciences         | 801   | 21     | 162    | 618    |
| D      | Earth Sciences        | 166   | 7      | 94     | 65     |
| E      | Engineering and Materials Sciences | 138 | 13    | 118    | 7      |
| F      | Information Sciences  | 100   | 7      | 88     | 5      |
| G      | Management Sciences   | 107   | 4      | 57     | 46     |
| H      | Medicine Sciences     | 456   | 29     | 427    | 0      |
| -      | Total Disciplines     | 2478  | 95     | 1062   | 1321   |

### 4 Experiments

#### 4.1 Dataset Description

We collected research proposals written by the scientists from 2020’s NSFC research funding application platform, containing 280,683 records with 2494 ApplyID codes. Among them, 7% are IR proposals containing two major disciplines, and the rest are marked as NIR. In data processing, we filtered the incomplete records and grouped the documents in each research proposal by
Table 2  The details of two datasets, NSFC-All and NSFC-IR.

| Dataset          | NSFC-All | NSFC-IR |
|------------------|----------|---------|
| Total Proposal Number | 280683   | 20632   |
| #Avg. Labels Length  | 2.393    | 3.397   |
| #Avg. Labels Num in Level-1 | 1.073    | 2.000   |
| #Avg. Labels Num in Level-2 | 1.197    | 2.000   |
| #Avg. Labels Num in Level-3 | 1.364    | 1.985   |
| #Avg. Labels Num in Level-4 | 0.477    | 0.808   |

the type of text. We chose four parts of a research proposal as the textual data: 1) Title, 2) Keywords, 3) Abstract, 4) Research Field. The Abstract part is a long text, and the average length is 100. The rest three documents are short text. All those documents are critical when experts judge the belonging disciplines of the proposal. We further removed all the punctuation and padded the length of each text to 200. Then we added a type-token at the beginning of each document to mark its particular type (just like the [CLS] token in the Bert [28]). For the label construction, we generated the topic path (as described in Section 2.1.3) of each research proposal from their ApplyID codes. Finally, these eight major disciplines are obtained, and the number of their sub-disciplines is also shown in Table 1.

To evaluate the impact of the imbalanced dataset and the performance of H-MixUp, we constructed two datasets:

- **NSFC-All**: We constructed NSFC-All as the dataset that contains all kinds of research proposals. As we mentioned before, NSFC-All is an imbalanced dataset. NSFC-All is built to train the models and illustrate the overall performance on an imbalanced dataset.
- **NSFC-IR**: The NSFC-IR only contains the IR proposals that including in the test set of NSFC-All (i.e., NSFC-IR ⊂ NSFC-All). Due to the IR data being the minority of all research proposals, so we can illustrate the imbalanced problem and the improvement of H-MixUp on the model by comparing the evaluation results between NSFC-IR and NSFC-All.

In Table 2, we counted the lengths of each label sequence and the average number of labels in each level on these datasets. Generally speaking, from NSFC-All to NSFC-IR, its text data exhibit interdisciplinarity increasingly.

4.2 Baselines

We selected HIRPCN and two groups of baseline methods to show the impact of the imbalanced data issue in the IRPC task. The first group is the Text Classification (TC) methods which aim to design a sophisticated encoder to utilize the semantic information fully. In general, the TC methods will treat the hierarchical structure flatly. The selected TC baselines are listed as follows:

- **TextCNN** [29]: TextCNN is a convolutional neural network based TC methods.
- **DPCNN** [30]: DPCNN is a deep pyramid convolutional neural network based TC methods.
• **FastText** [31, 32]: FastText model is an n-gram based TC method with a light architecture.

• **TextRNN** [33]: TextRNN is a bi-directional long-short-term-memory [34] recurrent-neural-network (Bi-LSTM-RNN) based TC model.

• **TextRNN-Attn** [35]: TextRNN-Attn uses an attention layer to aggregate the feature from each step of Bi-LSTM-RNN. Then provide the text classification results.

• **TextRCNN** [36]: TextRCNN is a recurrent convolutional neural network based TC model.

• **Transformer** [24]: We adopt the transformer model as a baseline method.

The second group is the HMC methods with the top-down design. Like HIRPCN, those HMC methods will generate each level’s discipline step by step. The selected HMC baselines are listed as follows:

• **HMCN-F** and **HMCN-R** [37]: HMCN-F is an HMC model that uses a feed-forward network and hybrid prediction layer. HMCN-R is an RNN-like variant of HMCN-F.

• **HARNN** [38]: HARNN consists of an LSTM-based encoder and a hierarchical attention-based memory unit as the classifier. The classifier unit preserves the last prediction result to generate the next prediction.

Besides those baselines, we selected the original HIRPCN and four H-MixUp variants of HIRPCN strategies to evaluate the improvement of H-MixUp.

### 4.3 Training Detail

We set the SIE layer number $N_e$ to 8, the hidden dimension size $h$ to 64, and the multi-head number to 8, the layer number $N_g$ of GCNs in IKE to 1 and the layer number $N_d$ in IF to 8. We use Word2Vec [39] model with a dimension $(h)$ 64 to generate the word embedding for each Chinese character. For the detail of training, we use Adam optimizer [40] with a learning rate of $1 \times 10^{-3}$, and set the mini-batch as 512, adam weight decay as $1 \times 10^{-7}$. The dropout rate is set to 0.1 to prevent overfitting. We set the warm-up step as 1000. All methods are implemented by PyTorch 1.8.1 [41]. The experiments are conducted on a CentOS 7.1 server with an AMD EPYC 7742 CPU and 8 NVIDIA A100 GPUs.

### 4.4 Evaluation Metrics

To fairly measure HIRPCN with other baselines, we evaluate the prediction results with several widely adopted metrics [42–44] in the domain of Multi-label Classification. For all experiments, we conducted a 5-fold cross-validation and reported the average recommendation performance, i.e., the **Precision** (P), the **Recall** (R), and the **F1 Score** (F1).
**Table 3** The Overall Model Performance with Each Training Strategies. The best results are highlighted in **bold**. The second-best results are highlighted in *underline*.

| Model               | Performance on NSFC-All | Performance on NSFC-IR |
|---------------------|-------------------------|------------------------|
|                     | F1   | P    | R    | F1   | P    | R    |
| TextCNN             | 0.453 | 0.455 | 0.450 | 0.373 | 0.495 | 0.299 |
| DPCNN               | 0.376 | 0.364 | 0.390 | 0.321 | 0.407 | 0.266 |
| FastText            | 0.459 | 0.451 | 0.467 | 0.381 | 0.493 | 0.311 |
| TextRNN             | 0.403 | 0.405 | 0.402 | 0.334 | 0.443 | 0.268 |
| TextRNN-Attn        | 0.409 | 0.411 | 0.408 | 0.339 | 0.448 | 0.272 |
| TextRCNN            | 0.423 | 0.423 | 0.423 | 0.357 | 0.469 | 0.288 |
| Transformer         | 0.369 | 0.356 | 0.382 | 0.310 | 0.394 | 0.256 |
| HMCN                | 0.679 | 0.656 | 0.685 | 0.541 | 0.683 | 0.448 |
| HMCN-R              | 0.594 | 0.593 | 0.594 | 0.469 | 0.612 | 0.380 |
| HARNN               | 0.686 | 0.676 | 0.696 | 0.546 | 0.700 | 0.448 |
| HIRPCN (Original)   | 0.749 | 0.726 | 0.774 | 0.615 | 0.763 | 0.516 |
| + Word-level MixUp  | 0.781 | 0.758 | 0.805 | 0.704 | 0.827 | 0.613 |
| (α = 0.5)           |       |       |       |       |       |       |
| + Word-level CutMix | 0.727 | 0.724 | 0.731 | 0.643 | 0.812 | 0.533 |
| (α = 0.5)           |       |       |       |       |       |       |
| + Manifold MixUp    | 0.767 | 0.762 | 0.773 | 0.655 | 0.815 | 0.548 |
| (α = 0.1)           |       |       |       |       |       |       |
| + Document-level MixUp | 0.761 | 0.739 | 0.785 | 0.669 | 0.792 | 0.579 |

### 4.5 Experimental Results

In this section, we conducted several experiments to evaluate the improvement of the H-MixUp and answer the following questions: **Q1.** How does the data imbalance affect the model performance, and can H-MixUp help HIRPCN overcome the data imbalance issue? **Q2.** How good is each level’s performance with different H-MixUp strategies? **Q3.** In terms of training loss and test loss, why can H-MixUp improve the performance of HIRPCN? **Q4.** In the view of the attention mechanism, why can H-MixUp enhance the performance of HIRPCN? **Q5.** What is the best $\alpha$ for each H-MixUp method?

#### 4.5.1 RQ1: Overall Performance Comparison

In Section 4.1, we introduced two dataset NSFC-All and NSFC-IR. The NSFC-All contains all records and has a severe data imbalance problem between IR data and NIR data. The NSFC-IR only contains the IR data in the test set of NSFC-All. We first trained the baseline methods, HIRPCN, and four H-MixUp strategies on the imbalanced dataset NSFC-All. Then we tested each methods on NSFC-All and NSFC-IR and reported the results in Table 3.

First of all, we noticed that the performance of every method declined compared from NSFC-All to NSFC-IR. This phenomenon shows that this data imbalance occurs whether the model predicts flatly (i.e., TC methods) or follows a top-down fashion (i.e., HMC methods and HIRPCN). In detail, the F1 score of each TC method deteriorated by -14.6% (DPCNN) to -17.6% (TextCNN), and so did the HMC (-20.3% to -21.2%) methods and HIRPCN (-17.8%). This deterioration demonstrated the severe problem raised by the data imbalance between IR and NIR data. Also, we found that the Recall (R)
declined much dramatically compared to the Precision (P), which resulted in
the deterioration of the F1 score. This phenomenon showed the same situation
as we illustrated in Figure 2 of Section 1 (i.e., the imbalanced data will lead
the model to predict incomplete label paths for IR data). Compared to the TC
methods, we found that the margin of deterioration in HMC methods is much
larger. We interpreted this was due to the HMC methods being more focused
on the design of sophisticated classifiers, so they are much easy to degenerate
when the label number is imbalanced.

Secondly, we noticed the general deterioration of the HIRPCN equipped
with different H-MixUp strategies (i.e., -9.8% to -14.6%) is lower than other
methods and much better than the original HIRPCN (+4.5% to +14.4%).
This phenomenon proves that introducing the H-MixUp will alleviate the data
imbalance issue during the training process. Besides this, the experimental
results also showed the F1 score and other measurements are improved. Com-
pared to the original HIRPCN, Word-level MixUp (+4.27%), Manifold MixUp
(+2.4%), and Document-level MixUp (+1.6%) are all achieved a higher F1 in
NSFC-All. This phenomenon indicates that the H-MixUp strategy can improve
the ability to categorize the IR data by utilizing the mixed NIR data. Apart
from that, the mixed feature can also improve the model performance for NIR
data. Except these, among all H-MixUp strategies, Word-level MixUp achieves
the best F1 score, indicating that Word-level MixUp is the best H-MixUp
strategy for the IRPC task. We also notice that Word-level CutMix performs
worse than other H-MixUp strategies. Therefore, We believe that concatenat-
ing the text to mix the feature will cause a severe loss of semantic information
in the text classification task, thus impacting the model performance.

![Model Performance on NSFC-All](image1)
![Model Performance on NSFC-IR](image2)

**Fig. 6** Level-wise prediction results of HIRPCN and HIRPCN with H-MixUp strategies.

### 4.5.2 RQ2: Level-wise Performance Comparison

We further reported the performance of level-wise prediction on the *NSFC-
All* and *NSFC-IR* in Figure 6. From the research funding administrators’
perspective, the accuracy of the last label should be the most important
because the finest-grain categorization would significantly improve the reviewer
assignment. Based on the results in Figure 6, we can draw the following conclusions.

Firstly, the performance of each model tended to decrease with the depth of level increased. This phenomenon is because the number of categories increases rapidly while the depth goes deeper, making the classification task harder.

Second, We noticed that with the level going deeper, the performance of the original HIRPCN becomes much worse than HIRPCN with different H-MixUp. The reason is that the data imbalance made the target label number decrease sharply in the dataset’s last two levels while the candidate label number increased. And HIRPCN with H-MixUp can handle this well, proving that our proposed strategy can enhance the model performance in the imbalanced dataset. Compared to all other H-MixUp strategies, Word-level MixUp achieves the most balanced performance on each level and the best performance on the last level. The results for Word-level MixUp here are also consistent with the results in Table 3.

4.5.3 RQ3: Discussion on the Training Loss and Test Loss
In this section, we give a discussion on H-MixUp strategies from the perspective of the loss. We showed the training loss and test loss change in each epoch during the model training in Figure 7. Figure 7(1) shows that the original HIRPCN’s training loss decreased. In contrast, the test loss increased during
the training process, showing how the IRPC task’s data imbalance drags the model performance and causes severe overfitting. However, in Figure 7(2-5), we notice that HIRPCN with different H-MixUp strategies has a drastic up and down in training loss with a steady decreasing test loss by introducing a randomly mixed feature. Thus, it is safe to say that introducing the H-MixUp will enhance the model generalization and training stability for the imbalanced dataset. Furthermore, we compared the test loss developing of each strategy in Figure 7(6), showing that the test loss in Word-level MixUp decreased more efficiently and was the same as the F1 score performance in the previous section.

4.5.4 RQ4: Attention on Research Proposal

We further discuss how the H-MixUp affects the attention mechanism on the text data. In Figure 8, we illustrated the title of an interdisciplinary research from the Life Sciences and the Information Sciences. We first colored the Information Sciences-related (Info-related) keywords red and the Life Sciences-related (Bio-related) keywords green, then fed the selected text sequence into the original HIRPCN and HIRPCN with four H-MixUp strategies. The middle part of the figure showed the model’s attention value to this sequence, and the right side of this figure illustrated the proportion of the model’s attention to the different domains. From the figure, we can observe that except for HIRPCN with Word-level CutMix, all other models gained more attention on the domain-related keywords such as 遗传变异 (Genetic Variation) and 深度挖掘算法 (Deep Mining Algorithm), proving that HIRPCN can capture the critical part of the input research proposal. We speculate that the CutMix-based H-MixUp performed worse due to its concatenating of text, undermining the sequence’s positional information and dragging the self-attention mechanism, which is consistent with the result in Table 3.

On top of that, we found that the MixUp-based H-MixUp will enhance the model to capture the critical words more efficiently, e.g., the proportion of colored shading in Word-Level MixUp is more significant than the original one. We speculate that the MixUp technique will bring more combinations of the text and the discipline information so the model can better learn and capture the unique critical part of the research proposal. Besides this, compared to the other H-MixUp strategies, the H-MixUp on the word-level place more balanced attention on the two domain-related keywords than the Document-level MixUp or the Manifold MixUp. We conclude that the more former level of feature mix in Transformer training will help the model get more balanced attention. Based on the above discussion, we summarize that HIRPCN with Word-level MixUp gains the highest F1 scores due to its most balanced attention to the text sequence and better capture of domain-related keywords.
4.5.5 RQ5: Hyperparameter Study

We conducted experiments to evaluate the effect of the critical hyperparameters $\alpha$ of the Beta distribution in Equations 7 and 8. We reported the results in Figure 9 and used the best $\alpha$ in the performance comparison.

![Fig. 9](image_url) Impact of different $\alpha$ selection in the Beta distribution.

5 Related Works

5.1 Imbalance Learning

The class imbalanced problem is common in real-world scenarios and has become a popular topic of research [45]. The mainstream imbalance learning algorithms can be divided into three categories: data-level, algorithm-level, and hybrid methods. Usually, the data-level methods adjust class sizes by down-sampling or over-sampling [46, 47]. The algorithm-level methods aim to directly increase the importance of minority classes through appropriate penalty functions [48, 49]. Lastly, hybrid systems strategically combine sampling with algorithmic methods [50]. However, there is little research on deep learning with class imbalanced data [51]. In this paper, we mainly focus on solving the hierarchical multi-label imbalanced problem for the research proposal data with Mixup-based algorithms [8].
Mixup-based methods has proven superior for improving generalization and robustness of deep neural networks [52] by interpolating features and labels between two random samples. Mixup [8] and its numerous variants (e.g. Manifold Mixup [53], Cutmix [21], etc.), as data augmentation methods, have not only achieved notable success in a wide range of machine learning problems such as supervised learning [8], semi-supervised learning [54, 55], adversarial learning [56], but also adapted to different data forms such as images [57], texts [58, 59], graphs [60], and speech [61]. Notably, to alleviate the problem of class imbalance in the dataset, a series of methods [9, 10, 62] employ Mixup to augment the data. Despite this, there has not been any research on using MixUp to solve the class imbalance problem in hierarchical multi-label classification.

6 Conclusion

This paper proposed H-MixUp, a hierarchical multi-label classification MixUp method for the IRPC task on the imbalanced real-world research proposal dataset. The main idea is to mix the input semantic feature and the previous prediction result during the training process to generate the pseudo interdisciplinary research proposal for training, then improve the data imbalance. We evaluated four H-MixUp strategies, and the results showed that each can improve the model performance. We also found the best strategy as Word-level MixUp by overall comparison and level-wise comparison. In the rest experiment, we further explored why H-MixUp could improve the model performance from the perspective of the training loss and test loss and the attention mechanism of input text. As we hope, the H-MixUp strategies will improve the data imbalance issue and model generalization during the training process by providing a constantly high training loss. The results also showed that the MixUp method on the word level will give the most balanced attention to the domain-related keywords. Both observations proved the performance comparison results are reasonable. With the H-MixUp strategy, our proposed model can provide precise results on each level, significantly enhancing the reviewer assignment system in research funding management.

7 Declarations

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Conflict of interest The authors declare that they have no competing interests.
Ethical approval Study procedures were approved by the institutional review board of the University of the Chinese Academy of Sciences, and procedures were consistent with the Declaration of Helsinki. Use of experimental animals and human participants - The article does not report experiments on live vertebrates and/or higher invertebrates and only involves secondary analysis of de-identified data from NSFC.

Consent to participate The study protocol involved automatic consent from participants regarding using the study data in a de-identified form for secondary analysis.

Consent for publication All data generated or analysed during this study are included in this published article.

Availability of data and material The de-identified data is shared on: https://www.dropbox.com/s/4u4py7m3ssrt4hn/data.de.zip.

Code availability The code of H-MixUp is shared on: https://www.dropbox.com/sh/1vh8na9z4ec4trb/AABbNqfAerDRsO52rd66s4xa.

Authors’ Contributions Conceptualization: MX, MW, ZQ, YF; Methodology: MX, ZQ; Formal analysis and investigation: MX, MW, ZN; Writing - original draft: MX, ZQ, ZN; Writing - review and editing: MX, YF, MW, ZQ; Funding acquisition: YZ, YD; Resources: YZ, YD, MX; Data acquisition: YD, MX; Supervision: YZ, YF. All authors read and approved the final manuscript.

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