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# Enhancing Early Detection of Fake News on Social Media with a Dual-Branch Neural Network Model

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**Abstract—** The widespread dissemination of fake news on social media has brought about the various degrees of negative impact on society. To address the issue of insufficient social context data in the early identification of erroneous information, we suggest a model that combines dual-branch network training. A max-pooling branch (MPB) and a generalised mean pooling branch (GPB) are the two main parts of this approach. While the GPB adds trainable pooling layers to capture the underlying semantic qualities of news articles, the MPB uses a convolutional neural network to extract text attributes from the articles. Additionally, every branch network evaluates the semantic importance of the news headline about the body text. Ultimately, judgements about the veracity of the news are based on the combined output of these two branch networks' cooperative training. The experimental results show that the suggested model outperforms baseline models in evaluation metrics such as accuracy, recall, and F1- Score, with an astounding F1- score of 94.1%.

***Keywords—*** *Fake News Detection; Social Media; Dual-Branch Network; Early Detection; Text Features; Semantic Relevance; Convolutional Neural Network; Generalized Mean Pooling.*

## 1. Introduction

In the internet era, the rapid development of online social media platforms such as Twitter, Weibo, and WeChat has provided readers with convenience in accessing news and information Kumar et al. (2023). Still, it has also created a breeding ground for the spread of fake news. In 2022, the WeChat (Li et al. 2020; Shi et al. 2021) platform published 17,881 debunking articles, which received 114 million views. Among them, medical health, food safety, and social sciences were the high-incidence areas for fake news. The proliferation of fake news has brought various degrees of negative impact on society and people's daily lives (Rohera et al. 2022). Such false news stories led to a rush to buy related products, misleading the public and disrupting the market economy. Xia et al. (2023) pointed out that fake news spreads faster and more frequently than real news. Therefore, the detection of fake news is of great importance.

The initial detection of fake news (Gupta et al. 2022;Zhu et al. 2023) primarily relied on official debunking websites, where numerous experts in relevant fields judged the authenticity of news. This approach required expert knowledge, consuming substantial human and material resources and suffering from poor timeliness. Automatic fake news detection techniques based on machine learning and deep learning have significantly progressed in recent years (Gupta et al. 2022). Currently, fake news detection methods can be broadly categorized into content-based (Capuano et al. 2023)and context based detection methods Seddari et al. (2022). The critical distinction between these two approaches is their utilization of social context information(Obaid et al. 2023). For instance, social context information includes the dissemination paths of news on social media, the relational networks among social users, and the engagement of social users (likes, shares, comments), among other factors. The richer the social context information, the more advantageous it is for fake news detection.

However, context-based fake news detection methods eddari et al. (2022) are not suitable for the early detection of fake news. The social context information is insufficient when news is initially published on news channels but has not yet spread

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on social media. Early detection of fake news holds practical significance because as fake news becomes more exposed and repeatedly appears in the view of social media users, they are more likely to believe its authenticity. Once users perceive fake news as true, it becomes challenging to change their perception.

Content-based detection, on the other hand, does not require consideration of social context information. This makes data acquisition easier and enables early detection of fake news. As a result, it has attracted increasing attention. Existing research typically treats news text content as a whole when performing fake news detection, with less emphasis on the semantic relationship between news headlines and the body text. Suppose a news article is not based on actual events. In that case, it often uses sensational and provocative headlines to attract readers, which are often unrelated to the article's content. While news articles with sensational headlines are generally considered unreliable, not all of them are necessarily fake news. This prompts further exploration of the relationship between fake news and "clickbait" headlines.

To address the aforementioned issues, this paper proposes a fake news detection model based on joint training of a dual-branch network (DBN). This model consists of two branch sub-networks: the Max Pooling Branch (MPB) and the Generalized Mean Pooling Branch (GPB). The MPB utilizes a convolutional neural network for text feature extraction, while the GPB, built upon the convolutional neural network, introduces trainable pooling layers. These two branch sub-networks are jointly trained to learn the underlying semantic features of news content collectively. Semantic relevance measurement is conducted between the news headlines and the body text within each branch subnetwork. Finally, the results obtained from the joint training of the two branch sub-networks are fused for decision-making, yielding the model's predictive output.

## 2. Related Work

### 2.1 Content-based Fake News Detection

Content-based fake news detection methods refer to using news content for detection, including textual information (headlines, body text, web links), visual information (images, emojis), audio information, etc. Most existing research has primarily focused on the textual content of news, extracting statistical or semantic features from it (Wang et al. 2023).

Zeng et al. (2023) employed language features based on news textual content to detect fake news. They designed a list of language features, such as question marks, emoticons, positive/negative sentiment words, and pronouns, to measure the credibility of information on Twitter. Guo et al. (2023) found that the language style of an article plays a crucial role in understanding its credibility.

However, features based on language style do not inherently carry semantic information and are susceptible to manipulation. Bera et al. (2023) used context independent grammar rules to identify fake information. Luvembe et al. (2023) explored representing news through deep neural networks by capturing temporal language features. Kakuba et al. (2022) introduced attention mechanisms into recurrent neural networks to focus on capturing distinctive temporal language features. With the development of multimedia technology, fake news attempts to attract and mislead readers by utilizing multimedia content with images or videos for rapid dissemination.

Wei et al. (2022) approached the issue from an image perspective, proposing a multi-domain visual neural network model that combines frequency domain and pixel domain visual information by exploring different features at the physical and semantic levels. This model is used for fake news detection, but its generalization ability across different datasets still requires further validation.

Sabitha et al. (2021) delved deeper into fake image analysis by merging pixel and frequency domain features as visual features. They also incorporated the physical attributes of images. Ultimately, through ensemble learning, they combined visual and physical features to detect fake news images.

Most content-based fake news detection approaches typically analyze news headlines and body text as a single entity to extract semantic and stylistic features (Xia et al. 2023). There has been relatively less research that directly approaches the issue from the perspective of" clickbait," specifically analyzing the differences and correlations between headlines and body text. Although there have been studies focused on detecting” clickbait” in news articles (Seddari et al. 2022), their primary goal is to identify whether news articles exhibit ”clickbait” phenomena.

Therefore, building on the concept of”clickbait” detection, this paper places particular emphasis on exploring the semantic correlation between news headlines and body text. It leverages the Maximum Mean Discrepancy (MMD) metric (Hosseini et al. 2023) to measure this correlation. Through the joint training of deep neural networks and various pooling operations, latent features are automatically extracted from the text to detect the authenticity of news articles.

### 2.2 Social Context-Based Fake News Detection

Social context-based fake news detection methods aim to identify fake news by exploring social context information related to the news. This includes how the news spreads on social media and user engagement with the news. The social connections established through interactions between social media users and news articles provide rich social context information. Social context information represents user involvement with the news on social media (Jiang et al. 2023), such as the number of followers, comments, likes, topic tags, and the network structure of shares and retweets.

Allein et al. (2023) classified fake news by utilizing user profiles on social media and the news propagation paths. Puraivan et al. (2023) modeled the news propagation path as a multivariate time series and used a combination of RNNs and CNNs to detect fake news. However, during the early detection phase of fake news, when news is published on news channels but has not yet spread on social media, relying on news propagation information is not feasible because it does not exist at that stage (Wu et al. 2023).

Palani and Elango (2023) used a tree-structured recursive neural model to learn representations of tweets. Gˆolo et al. (2023) employed manually extracted social context features such as follower count and retweet volume. Hua et al. (2023) analyzed users’ historical microblogs, combined user attributes and microblog text, and used the C-LSTM model for rumor detection. Shen Xiong et al. (2023) proposed a multi-task learning approach for Weibo rumor detection, leveraging sentiment analysis as an auxiliary task to address the issue of limited labeled data in deep learning. However, their model has a dependency on relevant auxiliary data.

Social context information is typically unstructured data that requires substantial manual effort to collect. Moreover, social context features need time to accumulate, making them unable to promptly detect newly emerging fake news. When news has not yet spread on social media, content-based detection methods are needed since rich social context information is not available during this stage. Therefore, this paper focuses on fake news detection based on the news content itself by mining potential information within it.

## 3. Proposed Methodology

The structure of the fake news detection model based on joint training of a dual-branch network proposed in this paper is illustrated in Figure 1. The model consists of two branch sub-networks: the MPB and the GPB. Each branch sub-network comprises three modules: (1) text feature extractor, (2) semantic relevance measurement between the headline and body text, and (3) fake news classifier.

Firstly, the text feature extractor independently extracts the features of the news article’s headline and body text. It employs MMD to measure the semantic relevance between these features. Subsequently, the two features are weighted and fused to serve as input to the fake news classifier. Finally, the classification results obtained from the joint training of the two branch subnetworks are combined, yielding the model’s predictive output (real or fake). MPB employs max pooling for down sampling, while GPB employs generalized mean pooling for down sampling.

### 3.1 Textual Feature Extraction

Given a news article, denoted as A = {T,B}, consisting of a title T and body text B, different text feature extraction methods are employed in the distinct branch sub-networks. In the MPB (Max Pooling Branch), this paper utilizes a Convolutional Neural Network (CNN) to learn feature representations of the news. Text-CNN utilizes multiple convolutional kernels with varying window sizes to capture textual feature information. For each word in the title T, its corresponding d-dimensional word embedding vector is represented as $xtlRd,l=1,2,\cdots,nt$. Here, the subscript t is used to denote the title T, while the subscript b is used for the body text B. The word embedding sequence for the news title can be expressed as:

$$T1:nt=x1\oplus x2\oplus\cdots\oplus xns \quad (1)$$

Among them, $T1:ntRni\times d,\oplus$ denotes the concatenation operation, and ntrepresents the length of the news title. A convolutional kernel with a window size of h takes a continuous sequence of h words from the title, denoted as $xti:(i+h\text{-}1)i=1n\text{-}h+1$ as input and performs convolution on it, resulting in the output feature map $Ct=Ctii=1n\text{-}h+1$. As an example, the convolution operation for a continuous sequence starting from the i-th word can be represented as in Equation (2):

$$cti=\sigma wtxti:(i+h\text{-}1)+bt \quad (2)$$

$$xi:(i+h\text{-}1)=xi\oplus xi+1\oplus\cdots\oplus xi+h\text{-}1 \quad (3)$$

In this context, $xti:(i+h\text{-}1)Rh\times d$, $\oplus$ represents the concatenation operation, wt denotes the convolution kernel, btis the bias term, and $\sigma(\cdot)$ represents the Rectified Linear Unit (ReLU) activation function. After the convolution operation, the obtained feature maps undergo max-pooling to achieve dimension reduction. The pooling layer extracts the maximum value from each feature map cti capturing the most important information.

After max-pooling, each feature map can be expressed as: $Ctm=maxctii=1n\text{-}h+1$ (4)

Finally, the pooled result is fed into the fully connected layer to obtain the feature representation of the obtained title :$Rtm=WtmCtm+btm$ (5)

In the above equations the subscript tm of Rtmindicates that the title feature is obtained through the MPB sub-network, Wtmrepresents the weight matrix, CtmRk,where k denotes the number of convolution kernels with different window sizes.

Similarly, for a news text B of length nb, after d-dimensional word embedding, it can be expressed as:

$$B1:nb=x1x2\oplus\cdots\oplus xnb \quad (6)$$

Using the same feature extraction method as the above news title, the feature representation of the body text can be expressed as:

$$Rbm=WbmCbm+bbm \quad (7)$$

The pooling layer of Text-CNN utilizes max-pooling operation, reducing the number of model parameters while maintaining position and rotation invariance of features. However, it neglects the positional information of text features. Wang et al. (2018) proposed a trainable generalized mean pooling layer (GeM pooling layer) that significantly improves retrieval performance. GeM pooling is between max-pooling and mean pooling, with both of them being special cases.

Therefore, in the GPB sub-network, based on the Text-CNN network structure, generalized mean pooling is used instead of the original max-pooling method to capture features of different granularities. For each feature map ct iobtained from Equation (2), generalized mean pooling is applied separately. The computation is represented as follows:

$$Ctg=ftgii=1n\text{-}h+1$$

$$ftgi=1ctixctixpi1pi \quad (8)$$

When pi = 1, generalized mean pooling is equivalent to mean pooling, and when $pi\rightarrow\infty$, generalized mean pooling is equal to max pooling. Compared to the max pooling, the generalized mean pooling includes a learnable parameter pi. It first calculates the pth power for the input sample ,then takes the mean value, and finally take the pth square root.

The pooled result is input to the fully connected layer to obtain the feature representation of the news title:

$$Rtg=WtgCtg+btg \quad (9)$$

In the above equations, the subscript tg of Rtg indicates that the feature representation of the title is obtained through the GPB subnetwork. Wtg is the weight matrix, and btg is the bias term.

Similarly, for news text B, the feature representation obtained through the GPB sub-network are expressed as:

Rbg=WbgCbg+bbg
(10)

### 3.2 Semantic Relevance Measurement Between Title and Body Text

A complete news article typically consists of a short title T and a long body text B. Inspired by the "clickbait" detection task, it is observed that creators of fake news often use sensational, exaggerated, or provocative titles to attract readers and promote false information. The content of the news body text often does not align with the title. However, solely detecting "clickbait" is insufficient, as some legitimate news articles may also exhibit "clickbait" characteristics. Therefore, in the text feature extraction process described above, two branch networks are used to fully explore the semantic information of news articles.

In the following sections, this paper employs the Maximum Mean Discrepancy (MMD) to measure the semantic relevance between the news title and the body text. MMD is a widely-used loss function in transfer learning, particularly in domain adaptation, used to measure the distance between two distributions in the Reproducing Kernel Hilbert Space (RKHS).

Assuming that the title and body text of a news article are derived from two semantic text distributions, denoted as XT and XB, respectively. If the title and body text describe the same event and are semantically related, then it is considered that they belong to the same distribution, and the news is

likely genuine. Conversely, if they are semantically unrelated, the news is considered likely fake. This paper employs MMD to measure the distance between the distributions of titles and body text, defined as follows:

MMDXT,XB=‖1XTxtXTxt-1XBxbXBxb‖ (11)

Here, ϕ(·) represents a mapping function used to map the original variables into the Reproducing Kernel Hilbert Space (RKHS). If a news article is fake, the MMD distance between its title and body text will be larger compared to genuine news, indicating lower relevance. The objective is to maximize the MMD distance between the title and body text of fake news articles. If this value is sufficiently small, it is considered that the two distributions are similar; otherwise, they are considered dissimilar. The MMD distance loss function can be represented as:

mmdT,B=MMD2XT,XB (12)

Where T = {tm, bg} represents the parameters required in the feature extraction process of news headlines, and B = {bm, bg} defines the parameters needed for the feature extraction process of news texts.

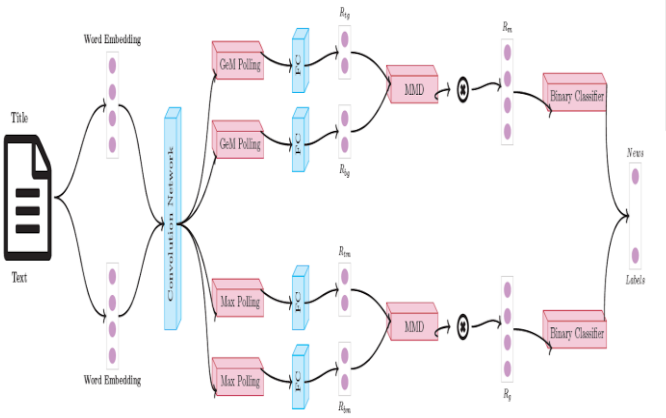


**Fig. 1:** Proposed framework for Fake User Identification

### 3.3 Fake News Classifier

So far, we have obtained feature representations for the news title and body text separately using the text feature extractors. In MPB, the feature representation of the title T is denoted as Rtm and the feature representation of the body text B is denoted as Rbm. In GPB, the feature representation of the title T is denoted as Rtg, and the feature representation of the body text B is denoted as Rbg. In each branch network, the title features and body text features are weighted and fused separately. The fused features are then used as input to the fake news detector, followed by a fully connected layer containing a Softmax function to predict the authenticity of the news. The fake news classifier can be represented as Ld·;d,where d, represents all the parameters in the classifier. For the i-th news article ai, the final output of the fake news detector is denoted as pai, representing the probability that the news article is fake.

pai=LdRmi,Rgi;d

Rm=1Rtm+2Rbm (13)

Rg=3Rtg+4Rbg (14)

Rm and Rg represent the features of an article after fusion in MPB and GPB. 1,2,3,4 represents the weights. The loss function ζd(θd) can be defined as:

class d=-Eai,y~(A,Y)ylogpai+(1-y)log1-pai (15)

Where $a_i$ represents an article, y represents the real label corresponding to the article. The goal is to find the optimal parameters dto minimize the classification loss. This process can be expressed as follows:

d=arg d class d (16)

### 3.4 Dual-branch joint training

To capture textual information in news articles from different scopes and granularities, a dual-branch network joint training method is employed, consisting of MPB and GPB branches. In each branch network, news title and body text features are extracted based on Text-CNN and different pooling methods. Then, the semantic distance between the title and body text is measured using MMD to constrain the two feature distributions. Finally, the two branch networks are jointly trained to output predictions for the fake news detection task. The purpose of doing this is to (1) detect fake news and (2) thoroughly explore the semantic relationship between the news title and body text. The final loss function of the model can be represented as follows:

final tm,bm,tg,bg,d=αclass d-βmmdmtm,bm+mmdgtg,bg (17)

Where class (·) represents the cross-entropy classification loss, mmdm (·) denotes the semantic association loss between the title and body text in MPB. tm and bm denote the parameters required in the title and text feature extraction process in MPB, respectively. Similarly, mmdg(·) represents the semantic association loss between the title and body text in GPB. Finally, tg and bg denote the parameters required in the title and text feature extraction process in GPB, respectively. The goal is to minimize the final loss function, which can be expressed as:

tm,bm,tg,bg,d=argtm,bm,tg,bg,d final tm,bm,tg,bg,d (20)

Among them, tm,bm,tg,bg,drepresent the parameters contained in the MPB sub-network, GPB sub-network and classifier, such as convolution kernel, weight matrix, bias term, etc. The above parameters are updated through the backpropagation algorithm, and the optimization process is shown in Algorithm 1. Each round of training uses the Adam optimizer to optimize the convergence speed of the network by adaptively adjusting the learning rate. During the training process, the Early Stop strategy is applied to halt training when the model's performance shows no significant improvement.

**Algorithm 1:DBN**

Input: news article A=Ti,Bii=1N, news label Y=yii=1N, learning rate η.

Output: Network parameters tm,bm,tg,bg,d.

1. Randomly initialize network parameters: tm,bm,tg,bg,d.

2. while not convergence do /*When the network does not converge*/

3. For each epoch do /* For each iteration, do the following steps */

4. For each mini-batch do /* For each batch, do the following */

5. Update the classifier parameters:

d⟵d-class d.

6. Update the parameters required in the process of extracting title features by the MPB subnetwork: tmtm-class tm-mmdmtm

7. Update the parameters required in the process of extracting text features by the MPB subnetwork: bmbm-class bm-mmdmbm

8. Update the parameters required for the GPB sub-network to extract title features

tgtg-class tg-mmdgtg

9. Update the parameters required for the GPB sub-network to extract text features:

bgbg-class bg-mmdgbg

10. end for

11. end for

12. end

13.Return network parameters: tm,bm,tg,bg,d.

## 4. Experimental Detail and Result Analysis

### 4.1 Dataset

To evaluate the performance of the proposed model in this paper, experiments were conducted using a publicly available news dataset. This dataset collected news articles published on WeChat public accounts from March 2018 to October 2018. The publicly available news dataset comprises six components: WeChat public account names (publishers), news headlines, news links, cover image links, user feedback reports, and news labels (fake or real). In order to explore the semantic correlation between news headlines and body text for the purpose of detecting fake news, further information gathering and data cleansing were performed on this dataset. Using the publicly available news links and cover image links, web scraping techniques were employed to retrieve the full text of each news article, cover images, and internal images. Many news articles, especially fake news, had become unavailable due to the regulation of WeChat's operational platform and reports from readers. Typically, news articles were either deleted or the public accounts were suspended, which made it impossible to retrieve all the complete data. Therefore, for articles that had become unavailable, only their headline information was retained.

The final statistics of the obtained data are shown in Table 1. In this paper, the news headlines and body text data were used as inputs for the model.

**Table 1.**Statistics of News Dataset

| Statistics | Fake news | Real news | Total |
|---|---|---|---|
| news article | 4225 | 16503 | 20728 |
| title | 4225 | 16 503 | 20728 |
| text | 918 | 8011 | 8929 |
| picture | 100068 | 118115 | 128183 |

### 4.2 Comparative experiment

To validate the effectiveness of the method proposed in this paper, commonly used methods in fake news detection tasks were selected as baseline methods for comparison.

(1) CNNT (Nasir et al. 2021): CNNT uses only news headlines as input. Due to the absence of body text, the semantic correlation measurement between headlines and body text, as used in the DBNN model, is removed. It then employs a dual-branch network for feature extraction, followed by binary classification.

(2) CNN (Sastrawan et al. 2022): CNNB uses only news body text as input, with other settings similar to CNNT.

(3) LSTM (Bahad et al. 2019): LSTM employs a single-layer LSTM as a text feature extractor. It averages the outputs of the RNN at each time step to obtain latent representations, which are then fed into a fully connected layer for prediction. The fully connected layer outputs the probability that the news is fake.

(4)HAN (Wang et al. 2023): HAN constructs a hierarchical attention neural network framework for fake news detection based on the content of the news. It encodes the news content using a hierarchical structure of ”word-sentence-document” to represent an article, focusing on word-level attention at the sentence level and sentence-level attention at the document level.

(5) Att-RNN (Chen et al. 2023): Att-RNN leverages attention mechanisms to fuse text, visual, and social context features. In the experiment, visual and social context information is excluded, while the remaining parts are kept the same.

(6) EANN (Zeng et al. 2023): EANN consists of three main components: a multimodal feature extractor, a fake news detector, and an event discriminator. The multimodal feature extractor extracts text and visual information from posts. It learns recognizable feature representations together with the fake news detector for fake news detection. The event discriminator is responsible for removing event-specific features. Since the input contains only text information, the visual feature extractor and event discriminator are removed.

(7) SAFE: SAFE utilizes Text-CNN to extract text features from news articles. It detects fake news by computing the similarity between news article text and visual information. This model takes complete news articles as input and uses the same hyperparameters as described in literature (Capuano et al. 2023).

### 4.3 Evaluation Method and Parameter Settings

In this paper, we use Accuracy, Precision, Recall, and F1-score as evaluation metrics. Typically, a higher F1- score indicates better classifier performance. The experiments are conducted using the PyTorch deep learning framework to build the fake news detection model and perform model training. The dataset is split into training, validation, and test sets in a 7 : 1 : 2 ratio based on the publication dates of the news articles. Specifically, 70% of the data is used for training, 10% for validation, and 20% for testing, with the most recently published news articles included in the test data. Regarding parameter settings, the length of news headlines, denoted as $n_{t,}$ is set to 32, while the length of the body text, denoted as $n_b$, is set to 300. Any parts that fall short are padded with zeros, and any excess text is truncated. The embedding dimension d for both headlines and body text is set to 300. The final feature dimension after weighted fusion is 128 dimensions. Text-CNN employs three types of convolutional kernels with sizes of 2, 3, and 4, each with 200 filters. During network training, the Adam optimizer is used with a batch size of 256, 200 iterations, and a learning rate of 1×10−3. The mapping function $\phi(\cdot)$ in the MMD is a Gaussian kernel.

### 4.4 Results Analysis

Table 2 displays the experimental comparison results of our method with other methods. The experimental results demonstrate that our proposed method outperforms other methods in terms of accuracy, precision, and F1-score for fake news detection, achieving the best classification performance. Regarding the experimental results, the following points can be analyzed:

From the experimental results of CNN7 and CNNB, it can be observed that detecting fake news by using both news headlines and body text as inputs to the model performs better than using only headlines or body text as model inputs. This validates the effectivenessof measuring the semantic correlation between news headlines and body text.

**Table 2:** Comparison of Existing Model with Proposed Model

| **Method** | **Accuracy** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|---|
| CNNT | 0.981 | 0.936 | 0.875 | 0.905 |
| CNNB | 0.986 | 0.944 | 0.913 | 0.928 |
| LSTMs | 0.961 | 0.852 | 0.750 | 0.798 |
| HAN | 0.903 | 0.813 | 0.779 | 0.796 |
| Att-RNN | 0.953 | 0.891 | 0.620 | 0.731 |

| | | | | |
|---|---|---|---|---|
| EANN | 0.977 | 0.955 | 0.810 | 0.877 |
| SAFE | 0.985 | 0.944 | 0.908 | 0.925 |
| Proposed Model | 0.988 | 0.931 | 0.951 | 0.941 |

HAN employs word-level and sentence-level attention mechanisms to extract the most significant words and sentences in the article. While this approach works well for text classification, it is not suitable for fake news detection, as fake news is also structured around a topic. Relying solely on the most important information in the article is not effective in detecting fake news, leading to a lower F1-score in fake news prediction.

LSTM excels at handling sequential information and can better capture contextual information for text tasks. However, fake news detection tasks place greater emphasis on local features such as semantic style, and they do not heavily rely on sequential features. Therefore, the EANN model that uses Text-CNN for feature extraction performs better in extracting local features from text in fake news detection tasks.

SAFE extends Text-CNN by introducing additional fully connected layers to automatically extract text features from each news article. In contrast, our proposed method introduces trainable pooling layers, allowing the network to automatically adjust parameters during training and further learn potential text features of news. Hence, our method's overall performance is superior to SAFE.

Propound model uses a dual-branch network for joint training, enabling the comprehensive exploration of the latent semantic style features of news articles, thereby capturing the differences between fake and real news. Additionally, based on the concept of ”clickbait” detection, measuring the semantic correlation between news headlines and body text is effective in detecting fake news.

### 4.5 Comparison of Different Semantic Correlation Measurement Methods

To analyze the impact of different semantic correlation measurement methods on the experimental results, four variants were designed: (1) Removal of the semantic correlation measurement between headlines and body text (SCM). (2) Using CORAL [25] as the measurement method (CORAL). (3) Using cosine similarity as the

measurement method (COS). (4) Using the Maximum Mean Discrepancy (MMD) method proposed in this paper. The experimental results are shown in Table 3, indicating that among the four variants, the experimental results are best when using Maximum Mean Discrepancy (MMD) as the measurement method, followed by the use of cosine similarity as the measurement method. The results also demonstrate the effectiveness of measuring the semantic correlation between news headlines and body text in the task of fake news detection. The reason why Maximum Mean Discrepancy performs better than cosine similarity is that cosine similarity assumes that in the semantic feature space, the element features of two corresponding position vectors are aligned. However, this assumption is too strict and is often ineffective in heterogeneous source vectors. On the other hand, Maximum Mean Discrepancy maps two feature vectors into a reproducing Hilbert space, measuring the distance between two distributions through kernel learning methods. It does not require alignment of element features between two feature vectors, making it more suitable for measuring the semantic correlation between headlines and body text.

### 4.6 Comparison of Single-Branch and Dual-Branch Network Experimental Results

To explore whether the jointly trained dual-branch network model is more effective than training with a single branch network, this study conducted a comparative experiment between single-branch and dual-branch networks. Based on the DBNN model proposed in this paper, one of the branches was removed to create single branch networks. The experimental results are shown in Figure 2, where the MPB and GPB branches represent single-branch networks, and DBNN represents the dual-branch network. From the results in Figure 2, it can be observed that the dual-branch network achieves higher accuracy and F1-score compared to the single-branch network.

**Table 3:** Experimental results of different correlation measurement methods

| Measurement Method | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| MMD | 0.974 | 0.904 | 0.891 | 0.897 |
| CORAL | 0.982 | 0.923 | 0.908 | 0.915 |
| COS | 0.984 | 0.933 | 0.909 | 0.921 |
| MMD | 0.988 | 0.931 | 0.951 | 0.941 |

The F1-score of the dual-branch network is 0.016 and 0.015 higher than that of the MPB and GPB branches, respectively, demonstrating that joint training of the dual-branch network yields better results than training with single-branch networks.

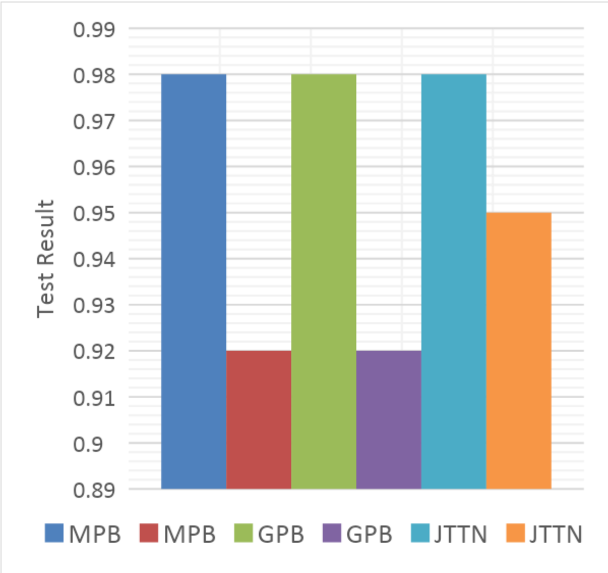


**Fig 2**. Comparison of experimental results between single-branch network and dual-branch network

**4.7 Impact of α and β on Model Performance**

In the loss function calculation formula (19), α and β are used to balance the relative importance between cross-entropy classification loss (α) and semantic correlation loss (β). To evaluate the impact of α and β on the model's performance, relevant experiments were designed. Different values of α and β were set, ranging from 0 to 1 with a step size of 0.2. Under different values of α and β, the model's detection results (accuracy and F1-score) are shown in Figure 3 and 4. It can be observed that, compared to α, different values of β have a more significant impact on the model's performance. When the value of β is relatively large, the model achieves higher accuracy and F1-score, indicating better classifier performance. Thus, the feasibility and effectiveness of measuring semantic correlation between headlines and body text in the model can be verified.

In Figure 3, the accuracy varies from 0.982 to 0.988,and the influence of different values of α and β on accuracy is not significant. In Figure 4, the F1-score ranges from 0.91 to 0.95, with a difference of 0.04. From the experimental results, it can be observed that the model performs best when $\alpha = 0.2$ and $\beta = 0.4$, or when $\alpha = 0.4$ and $\beta = 1$. In other words, when $\alpha : \beta \approx 1 : 2.3$, the model achieves the best performance.

**4.8 Convergence Analysis**

Figure 5 displays the variation of the final loss function value (loss) of the model proposed in this paper as a function of the number of iterations (epoch) during the training process. After approximately 20 iterations, the network gradually converges to a relatively stable trend. This confirms the effectiveness of the model proposed in this paper and the feasibility of the loss function calculation.

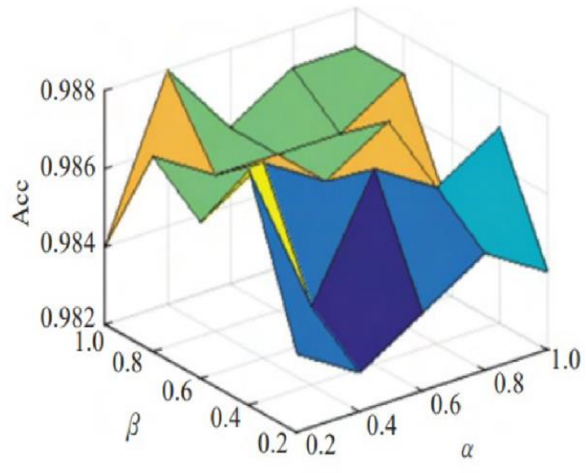


**Fig. 3:** Accuracy Rate on Loss function

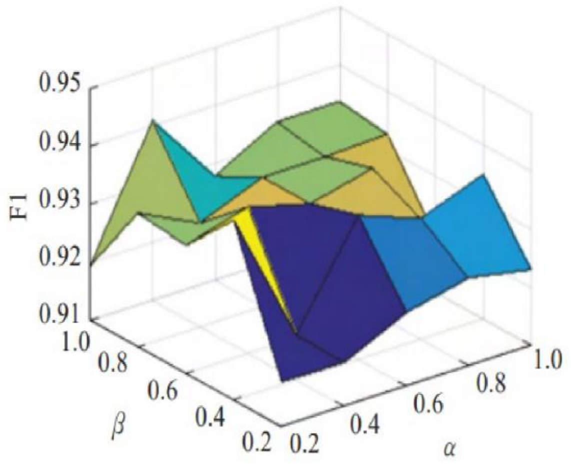


**Fig. 4:** F1-Score on Loss function

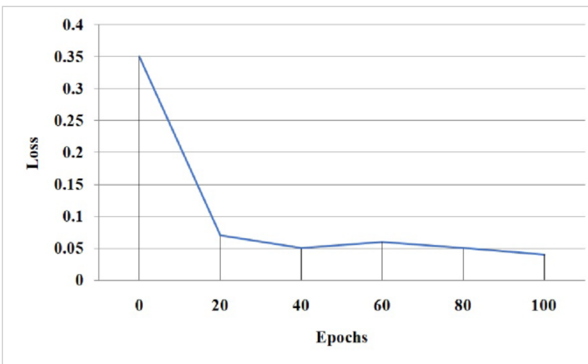


**Fig. 5:** Statistical Distribution of Loss Function

## Conclusion

The proposed method for detecting fake news based

on a dual-branch network with joint training leverages a dual-branch network structure to extract latent semantic features from news headlines and text bodies. Additionally, it measures the semantic correlation between headlines and text bodies to achieve early detection of fake news. The model in this paper has achieved good performance, with accuracy and F1-score reaching 0.988 and 0.941, respectively. Experimental results demonstrate the feasibility and effectiveness of the joint training approach based on a dual-branch network. Currently, this paper uses only text data (single modality) as the model's input. Future work will focus on expanding the types of input data by incorporating additional information from social media, such as images, videos, and other modalities, to enhance multi-modal fake news detection.

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