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ADAPTIVE SENSITIVE DATA RECOGNITION BASED ON INFORMATION INFERENCE IN SOCIAL NETWORKS

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ABSTRACT

The detection of sensitive information in social data of online social network members has become crucial with the advent of the multimedia era for ensuring the security of network community information. The entire semantic understanding of multimodal data and the ability to learn cross-information between data modalities cannot currently be acquired by classic sensitive information detection approaches in online social networks. It is crucial to research a new multimodal deep learning model that takes semantic links into account. The enhanced multimodal dual-channel reasoning mechanism (MDR) presented in this research mines semantic data and implicit association links between modalities in great detail. Based on taking multimodal data fusion into account. We also suggest a multimodal adaptive spatial attention method (MAA) to boost the decoder's precision and adaptability. In order to train and evaluate our algorithm, we manually annotated 50 users' actual social data. The experimental results confirm the viability and efficiency of a multimodal deep model considering semantic strategies in social network sensitive information identification and demonstrate that the proposed method significantly outperforms simple multimodal fusion deep learning models in terms of sensitive information prediction accuracy and adaptability.

Keywords: Adaptive, Sensitive, Recognition, Information, Inference, Social Networks.

I. INTRODUCTION

Because it impacts their capacity to regulate who may access their personal information and how that information can be used, privacy is a major concern for users of online social networks. Without adequate privacy protection, users may be vulnerable to others accessing or abusing their personal information, which might result in a number of negative outcomes including identity theft, financial fraud, or online harassment. Online social networks may make users feel comfortable using the network and contribute to network building trust and confidence by preserving user privacy. Additionally, online social networks themselves must prioritise user privacy. Users may be less likely to utilise a network if they believe their personal information is not sufficiently safeguarded, which might lower the network's user base and lower its overall worth. Online social networks may assist preserve and grow their user base, which is essential to their ongoing success, by preserving user privacy.

Although individuals can be hesitant to provide personal information, the connections that exist between public and private data frequently lead to major privacy violations. Once again, the 2021 Data Security Conference has drawn a lot of interest, and a number of data security voices have emerged. Uncompleted data indicates that since 2015, there have been more than 400,000 specialists working in the Internet black-gray sector. The following is the breakdown of this article. We will address the problems with finding sensitive material in online social networks in Section 1 and present our suggested solution.

Will give a summary of earlier studies on privacy protection in online social networks, concentrating on the issues and difficulties that drove our strategy. We shall discuss the user-sensitive data leaking issue that our work intends to address of this article. The approach to feature extraction, the enhanced multimodal semantic strategy, and the multimodal adaptive spatial attention mechanism are all covered in depth in Section 4 of the technique we suggest for finding sensitive information.

II. MULTIMODAL FEATURE FUSION

Since there are many different ways to disseminate data, there are many distinct data modes, hence the study of multimodal fusion is gradually being applied to many different research disciplines. The contribution of a single modal piece of data to the emotional outcome of sentiment analysis is not constant. The emotional characteristics of a particular natural language will be impacted by the natural language data when the temporal dimension is extended. The long-term reliance between modes was resolved by Qi et al. [35] by completely taking into account the long-term dependency between modes and the offset impact of nonnatural language data on natural language data. To simulate the interplay of many modes and accomplish the emotion prediction of multimode characteristics, Yan et al. [36] used a tensor fusion network.

A graph dynamic fusion module was suggested by Hu et al. [37] to combine multimodal context elements in the discussion. A feature fusion approach based on K-means clustering and kernel canonical correlation analysis (KCCA) was presented by Chen et al. [38], which outperforms previous approaches (such aware segmentation and tagging techniques) in terms of recognition rate. When dealing with fusion mode information, it is challenging for the model to efficiently employ all modes due to the intrinsic properties of each mode.

Problem Description

How to gather a sizable and varied collection of sensitive data is the first issue we must address. Due to the lack of frequently used and publicly accessible sensitive information datasets, this is a prevalent difficulty in the field of sensitive information identification. Because disclosing sensitive information may be against the law, all current sensitive information identification methods really rely on proprietary datasets that cannot be obtained for free.

We made the decision to manually gather and annotate actual data for the sensitive information recognition challenge in order to get around this constraint. As a result, we were able to produce a dataset that can be used to train and test our model without breaking any rules or laws. Here are three recent user social media postings that we think may divulge personal information and pose hazards.

Architecture

In the process of protecting privacy data on social networks, understanding user-sensitive information is a critical bottleneck, which typically requires analyzing the user’s historical resource data and historical access control settings to continuously adjust to determine the user’s sensitive preferences. This process requires multiple adjustments and inferences. Using a multimodal data bi-channel multihop reasoning mechanism to determine user-sensitive preferences can help to use the rich potential information between multimodal privacy data to generate access control privacy permissions.

We concentrate on enhancing Chen et al.'s [49] two-channel multihop inference mechanism's capability to extract sensitive data from user-posted resource data on social networks. First, we employ feature representations to represent the privacy information of historical writings and photos created by people. The two-channel multihop inference technique is used to repeatedly interact with all representations of modal privacy features.

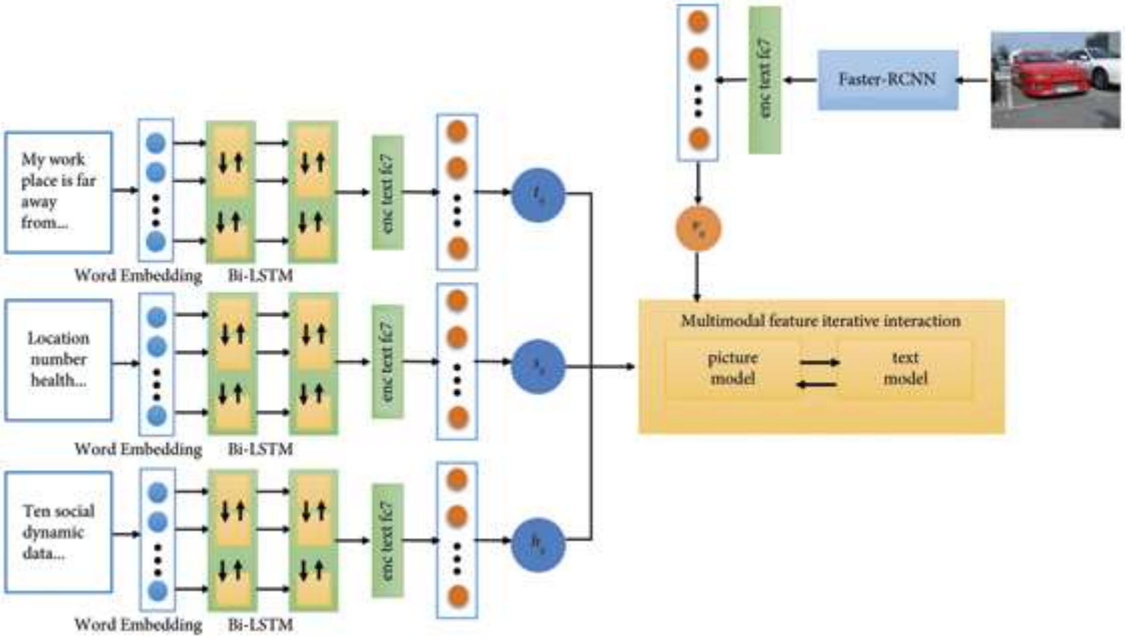

Fig.1: Adaptive Sensitive data Recognition Based on Information Inference in Social Networks Process.

III. MULTIMODAL SENSITIVE INFORMATION REASONING

Rich cross-modal information is also included in multimodal data, in addition to intermodal information. Most of the current multimodal deep learning algorithms first utilise a deep model to capture the private characteristics in the modality and merge the modality-specific original in order to learn the rich intermodality and intersectionality information in multimodal sensitive information data. A very abstract version of the representation of a certain global space is created. These highly abstract representations follow.

are further concatenated into a vector, which represents a multimodal global representation. Finally, a deep model is used to model the high abstraction of the connected vectors.

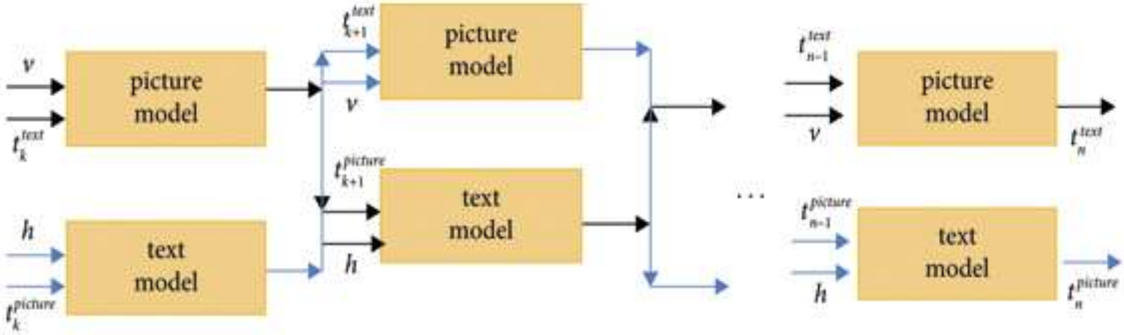

Fig.2: Adaptive Sensitive data Recognition Based on Information Inference in Social Networks Method

Attention Mechanism

Finding relevant information and suppressing irrelevant information is the core function of the attention mechanism. The value of each modality in a certain environment is determined by the attention mechanism in the multimodal spatial attention decoder. This means that the network can focus more on one mode than another, depending on the requirements of the specific task. For instance, if the network is attempting to recognise a word being spoken, it may focus more on audio data than visual data. After the neural network evaluates the significance of each modality, it combines data from all modalities to make more accurate predictions, which may involve just using simple statistical analysis. concatenating information from all modalities or may involve more complicated processing. The exact details of how a multimodal spatial attention decoder performs this fusion will depend on the specific architecture of the network.

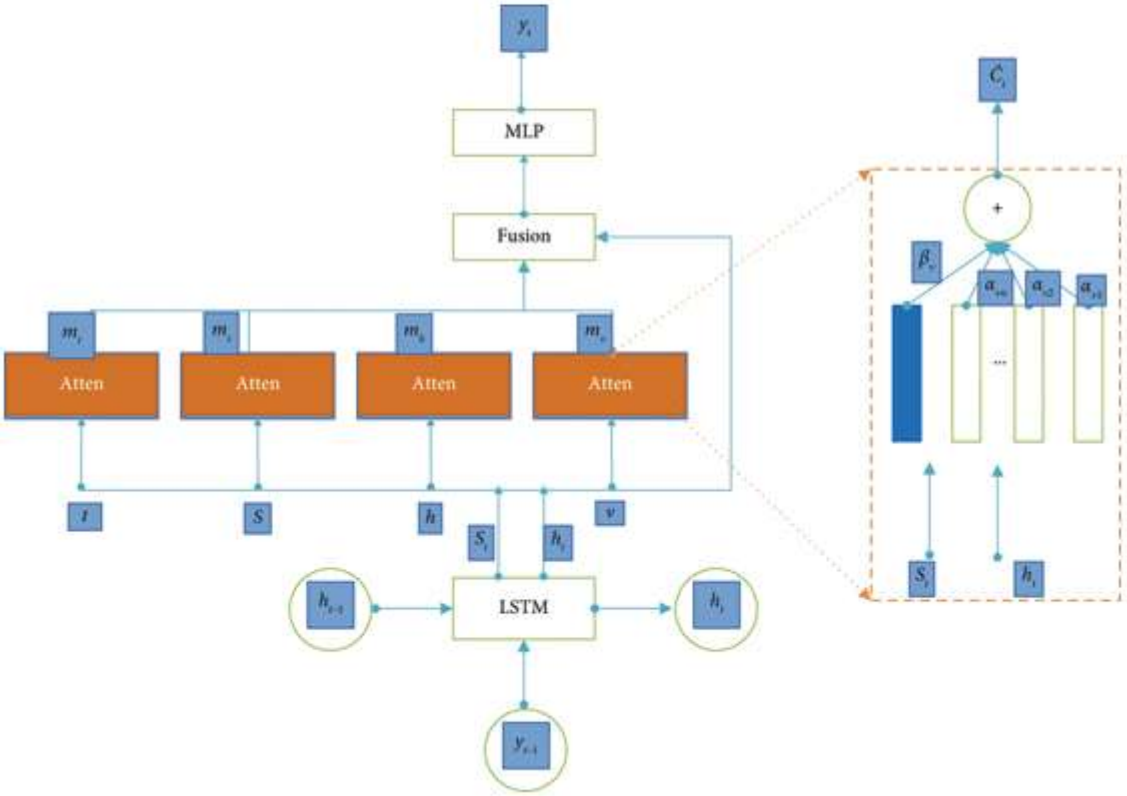

Fig.3: Adaptive Sensitive data Recognition Based on Information Inference in Social Networks

IV. RESULT

50 students' manually annotated data posts on social media are used to assess our trials. Each student has 120 pieces of data, each of which contains text, pictures, descriptions of the pictures, sensitive lists, and previous privacy settings. There are 6k pieces of such data in all, comprising 24,000 pieces of text and 6,000 pieces of images. The final training dataset has 4800 photos and 19,200 different types of text information. The verification set contains 600 images and 2,400 different types of text information, while the test set contains 600 images and 2,400 different types of text information. Multiple components make up the architecture of the model we provide.

And in this experiment, we compare our work with unimodal and multimodal models and evaluate the impact of our designed reasoning module and multimodal spatial attention mechanism on contribution to the final prediction accuracy. We train the following comparison models on our collected real-world data and show the performance of different comparison

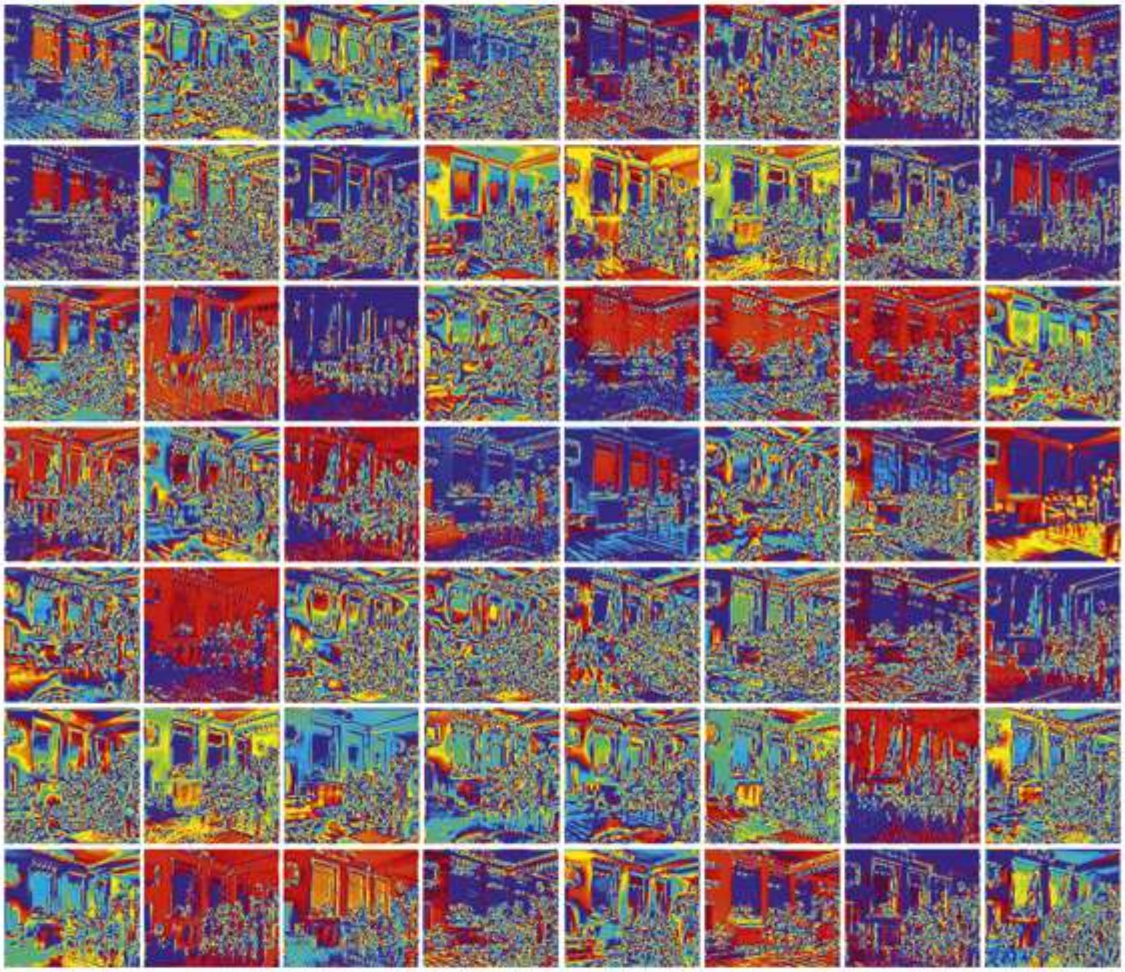

Fig.4: Adaptive Sensitive data Recognition Based on Information Inference in Social Networks Display

V. CONCLUSIONS

This research suggests a multimodal adaptive spatial attention decoder, which enhances the spatial attention decoder. On the user's past sensitive data, it integrates a dual-channel multihop reasoning architecture to do deep reasoning and prediction. In addition to enabling interaction between pictures and text, this method also permits a full investigation and use of their implicit relationships. By paying attention to the context and context information of text and visuals and adaptively switching focus between them when forecasting sensitive information.

The flexible and precise identification of sensitive user data is made possible by visual information and language models, and in our study from 50 volunteers, good results have been reached in the data gathered by the authors. In order to remove recognised privacy elements or establish relevant access privileges, this work will later be coupled with social network work access control.

The dynamic nature of data is another significant obstacle to preserving the privacy of online social network data, in addition to the absence of privacy semantics brought on by data variety. It might be challenging to protect privacy over time since data are always changing. Using conventional methods to learn from dynamic multimodal data, such as training a new model every time the data distribution changes, can be time-consuming and impractical for online applications. Therefore, online learning and incremental learning have emerged as promising real-time learning strategies for multimodal data fusion.

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