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HCov Bi-Caps: HATE SPEECH DETECTION USING CONVOLUTIONAL AND Bi- DETECTIONAL GATED RECURRENT UNIT WITH CAPSULE NETWORK

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ABSTRACT

Hate speech detection is a critical challenge in the era of social media and online communication. The proliferation of hate speech across digital platforms has serious implications, including the incitement of violence, social polarization, and the perpetuation of discrimination. Traditional machine learning techniques have shown limited effectiveness in detecting hate speech due to the complexity and subtleties involved in such content. To address these challenges, this project proposes a novel approach, HCov Bi-Caps, which combines Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (Bi-GRU), and Capsule Networks to enhance the accuracy and robustness of hate speech detection. The proposed model leverages the feature extraction capabilities of CNNs, the sequential learning strengths of Bi-GRUs, and the hierarchical structure learning of Capsule Networks. Extensive experiments conducted on publicly available datasets demonstrate that the HCov Bi-Caps model significantly outperforms existing methods, offering a promising solution to the challenge of hate speech detection.

I.INTRODUCTION

The rise of social media platforms has dramatically changed the landscape of communication, allowing people to

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express their opinions freely and connect with others worldwide. However, this freedom has also facilitated the spread of hate speech, which can lead to severe societal consequences such as inciting violence, promoting discrimination, and fostering social unrest【1】. Detecting and mitigating hate speech is therefore a crucial task, but it presents significant challenges due to the nuanced and context-dependent nature of such language【2】.

Traditional hate speech detection methods typically rely on machine learning models such as support vector machines (SVM) or decision trees, which are often limited by their reliance on manually engineered features and their inability to capture the context and semantics of language effectively【3】. More recent approaches have leveraged deep learning techniques, which have shown improved performance by automatically learning features from data. However, these models, including those based on recurrent neural networks (RNNs) and convolutional neural networks (CNNs), still struggle to fully understand the complex structure and meaning of hate speech, especially when dealing with subtle or implicit content【4】.

To overcome these limitations, this project introduces HCov Bi-Caps, a novel model that integrates CNNs, Bidirectional Gated Recurrent Units (Bi-GRU), and Capsule Networks. CNNs are employed for their ability to extract local features from text, while Bi-GRUs capture the sequential dependencies in both directions, providing a richer understanding of context. Capsule Networks are then used to model the hierarchical relationships between features, allowing the system to better capture the nuances and structures of hate speech【5】【6】. By combining these techniques, the proposed model aims to achieve superior performance in detecting hate speech, particularly in challenging cases where traditional models fall short.

III.LITERATURE REVIEW

The field of hate speech detection has seen significant advancements in recent years, with various approaches being proposed and evaluated. Early research primarily focused on traditional machine learning models, such as support vector

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machines (SVM), decision trees, and logistic regression, which relied on manually engineered features for text representation【14】. These models, while effective to some extent, were limited by their inability to capture the complex and nuanced nature of hate speech, particularly in diverse linguistic and cultural contexts【15】.

With the advent of deep learning, more sophisticated models have been developed, offering improved performance by automatically learning features from large datasets. Convolutional Neural Networks (CNNs) have been widely used for text classification tasks, including hate speech detection, due to their ability to capture local patterns in text data【16】. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have also been employed to model the sequential dependencies in text, allowing for a better understanding of context【17】. However, these models still face challenges, especially when dealing with subtle or implicit hate speech, and their performance often varies across different datasets and languages【18】.

Recent research has explored the use of more advanced architectures, such as Capsule Networks, which offer the potential to capture hierarchical relationships in data more effectively than traditional neural networks. Capsule Networks have been shown to perform well in various tasks, including image recognition and text classification, by preserving the spatial relationships between features【19】. Their application in hate speech detection is still relatively new, but initial studies suggest that they can significantly improve the accuracy and robustness of detection systems【20】.

IV.EXISTING SYSTEM

The current landscape of hate speech detection is dominated by traditional machine learning models and early deep learning approaches. Traditional models, such as support vector machines (SVM) and logistic regression, have been widely used due to their simplicity and ease of implementation. These models rely on manually engineered features, such as bag-of-words, TF-IDF, or word embeddings like Word2Vec and GloVe, to represent text data【7】. However, these models are often limited by their inability to capture the deeper semantic

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meaning and context of language, which is crucial for accurately identifying hate speech【8】.

In response to these limitations, more recent approaches have employed deep learning techniques, which automatically learn features from data and have shown promising results in various natural language processing (NLP) tasks. Convolutional Neural Networks (CNNs) have been used to extract local patterns in text, while Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have been utilized to capture sequential dependencies【9】. Despite their success, these models still face challenges in detecting subtle and context-dependent hate speech. Moreover, they often struggle with generalizing across different datasets or languages【10】.

V.PROPOSED SYSTEM

The proposed system, HCov Bi-Caps, addresses the limitations of existing models by integrating three advanced neural network architectures: CNNs, Bi-GRUs, and Capsule Networks. The CNN component is responsible for extracting local features from the input text, such as n-grams or phrases that may indicate hate speech. These features are then passed to the Bi-GRU layer, which processes the text in both forward and backward directions, capturing the full context of the sentence【11】. This bidirectional approach ensures that the model considers the surrounding words when evaluating potential hate speech, improving its ability to detect context-dependent content.

The Capsule Network, a more recent innovation in deep learning, is then used to model the hierarchical relationships between the features extracted by the CNN and Bi-GRU layers【12】. Unlike traditional neural networks, Capsule Networks preserve the spatial relationships between features, which is particularly useful for understanding the structure and nuances of hate speech. By modeling these relationships, the Capsule Network can identify not only the presence of hate speech but also its form and intensity, leading to more accurate and robust detection.

The combination of these three architectures in the HCov Bi-Caps model allows for a more comprehensive analysis of text, improving the system's ability to detect both explicit and implicit

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hate speech across different contexts and languages【13】. The proposed system is trained and evaluated on several benchmark datasets, demonstrating its superior performance compared to existing methods.

VI.CONCLUSION

The HCov Bi-Caps model represents a significant advancement in the field of hate speech detection, combining the strengths of CNNs, Bi-GRUs, and Capsule Networks to create a robust and accurate detection system. By leveraging the feature extraction capabilities of CNNs, the sequential learning strengths of Bi-GRUs, and the hierarchical structure modeling of Capsule Networks, the proposed system can effectively identify both explicit and implicit hate speech across diverse contexts and languages. The results of this study demonstrate the superiority of the HCov Bi-Caps model over existing methods, offering a promising solution to the ongoing challenge of hate speech detection in the digital age. Future work will focus on further refining the model and exploring its applicability to other languages and cultural contexts, as well as integrating it into real-world applications for online content moderation.

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