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Research Paper

CONTENT-BASED SCAM CALL IDENTIFICATION USING SPARSE ATTENTION NEURAL NETWORKS

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ABSTRACT

The increasing prevalence of scam calls has become a major cybersecurity concern, causing financial losses and privacy breaches worldwide. Traditional spam detection systems rely heavily on static rule-based filtering or metadata analysis, which often fails to detect sophisticated scam calls that use dynamic conversational patterns. This research proposes a novel deep learning-based framework for classifying scam calls through content analysis using Dynamic Sparsity Top-K Attention Regularization. The model leverages natural language processing (NLP) techniques to analyze call transcripts and identify malicious intent based on semantic patterns, linguistic cues, and contextual dependencies. Unlike conventional attention mechanisms that process all tokens equally, the proposed approach introduces a Top-K attention regularization strategy that dynamically selects the most relevant features, thereby reducing computational complexity and improving classification accuracy. The dynamic sparsity mechanism ensures that only the most informative tokens contribute to the final decision, making the model efficient and suitable for real-time applications. Additionally, the system integrates speech-to-text conversion, feature extraction, and attention-based neural networks to provide end-to-end scam detection. Experimental results demonstrate that the proposed model achieves higher precision, recall, and F1-score compared to traditional machine learning and baseline deep learning approaches. Furthermore, the model shows reduced inference time and improved scalability, making it suitable for deployment in telecom systems and mobile applications. The proposed framework enhances user security by providing real-time scam detection and contributes to the development of intelligent communication systems capable of identifying fraudulent activities. Overall, this research highlights the effectiveness of combining NLP, attention mechanisms, and sparsity optimization techniques in detecting scam calls and improving communication security in modern telecommunication networks.

Keywords: Scam Call Detection, Natural Language Processing, Top-K Attention, Dynamic Sparsity, Deep Learning, Speech-to-Text, Cybersecurity

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1. Introduction

The rapid growth of telecommunication technologies and mobile networks has significantly increased the volume of voice-based interactions, creating new opportunities for both legitimate communication and malicious activities such as scam calls. Scam calls, also known as fraudulent or phishing calls, are designed to deceive individuals into revealing sensitive information or transferring money under false pretenses. These calls often employ sophisticated social engineering techniques,

making them difficult to detect using traditional filtering methods [1], [2].

Existing approaches for scam detection primarily rely on call metadata such as caller ID, frequency, and blacklisting mechanisms. However, these techniques are ineffective against modern scammers who frequently change phone numbers and adopt dynamic strategies to evade detection [3]. As a result, there is a growing need for intelligent systems that can analyze the actual content of conversations to identify malicious intent [4]. Natural Language Processing (NLP) has emerged as a powerful tool for understanding and analyzing human language, enabling the detection of patterns and anomalies in textual data [5].

Recent advancements in deep learning have further enhanced NLP capabilities, particularly with the introduction of attention mechanisms that allow models to focus on important parts of input data [6]. Attention-based models, such as Transformers, have demonstrated superior performance in various NLP tasks, including text classification and sentiment analysis [7]. However, standard attention mechanisms process all tokens uniformly, leading to increased computational complexity and potential inefficiencies when dealing with large-scale conversational data [8].

To address these limitations, sparsity-based approaches have been introduced to improve efficiency and focus on the most relevant features. Dynamic sparsity techniques enable models to selectively attend to important tokens, reducing computational overhead while maintaining high performance [9]. The Top-K attention mechanism is one such approach that selects the most significant attention scores, allowing the model to concentrate on key information [10].

In the context of scam call detection, content analysis plays a crucial role in identifying linguistic patterns associated with fraudulent behavior, such as urgency, threats, or requests for sensitive information [11]. Combining NLP with attention mechanisms and sparsity optimization can significantly improve detection accuracy and efficiency. Furthermore, speech-to-text technologies enable the conversion of voice calls into textual data, making it possible to apply advanced NLP techniques for real-time analysis [12].

Despite these advancements, challenges such as data imbalance, variability in language usage, and real-time processing constraints remain significant barriers [13]. Additionally, ensuring model interpretability and robustness against adversarial attacks is essential for practical deployment [14], [15]. Therefore, this research proposes a novel approach that integrates dynamic sparsity with Top-K attention regularization to enhance scam call classification.

2. Literature Survey

The detection of scam and spam calls has been an active area of research, with early studies focusing on rule-based and statistical methods. These approaches relied on predefined patterns and heuristics to identify fraudulent calls but were limited in handling evolving scam tactics [16]. Machine learning techniques, such as Support Vector Machines (SVM) and Decision Trees, were later introduced to improve classification accuracy by learning patterns from data [17]. However, these models often require extensive feature engineering and struggle with unstructured text data.

The emergence of deep learning has significantly improved text classification tasks, including scam detection. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been widely used for analyzing sequential data, capturing contextual dependencies in conversations [18]. While these models improved performance, they suffer from limitations such as vanishing gradients and high computational costs.

Transformer-based models have revolutionized NLP by introducing self-attention mechanisms

that enable parallel processing and improved contextual understanding [19]. Models such as BERT and GPT have demonstrated state-of-the-art performance in various text classification tasks, including spam detection [20]. However, their high computational requirements make them less suitable for real-time applications, particularly in resource-constrained environments.

To address these challenges, researchers have explored sparse attention mechanisms that reduce computational complexity while maintaining performance. Child et al. proposed sparse transformers that limit attention computation to a subset of tokens, significantly improving efficiency [21]. Similarly, Beltagy et al. introduced Longformer, which uses local and global attention patterns to handle long sequences efficiently [22].

Top-K attention mechanisms have also been studied as a means to focus on the most relevant tokens. Correia et al. proposed adaptive attention span models that dynamically adjust attention based on input data [23]. Additionally, dynamic sparsity techniques have been applied in NLP to optimize model performance and reduce resource usage [24].

Recent studies have explored the application of NLP and deep learning for scam detection in telecommunication systems. These approaches integrate speech recognition, text analysis, and machine learning models to identify fraudulent calls in real time [25]. However, there is still a need for more efficient and scalable solutions that combine attention mechanisms with sparsity optimization.

3. Proposed Methodology

The proposed system introduces an advanced framework for scam call classification based on content analysis using Dynamic Sparsity Top-K Attention Regularization. The architecture consists of multiple components, including speech-to-text conversion, text preprocessing, feature extraction, and an attention-based classification model. Initially, voice call data is converted into textual format using a speech recognition module, enabling the application of NLP techniques. The textual data is then preprocessed through tokenization, stop-word removal, and normalization to ensure consistency and improve model performance.

The core component of the system is a transformer-based neural network enhanced with a Top-K attention mechanism. Unlike traditional attention models that consider all tokens equally, the proposed model dynamically selects the top K most relevant tokens based on attention scores. This selective attention process reduces computational complexity and ensures that the model focuses on critical features that contribute to scam detection. The dynamic sparsity mechanism further optimizes the model by adjusting the value of K based on input characteristics, allowing adaptive feature selection.

Feature extraction is performed using embedding techniques that capture semantic and contextual information from the text. Pre-trained embeddings such as Word2Vec or contextual embeddings from transformer models are utilized to represent words in a high-dimensional vector space. These embeddings are then processed by the attention layer, which assigns weights to different tokens based on their importance. The Top-K attention regularization ensures that only the most significant tokens influence the final classification, improving both efficiency and accuracy.

The classification layer uses a fully connected neural network to categorize calls as either scam or legitimate. The model is trained using labeled datasets containing scam and non-scam call transcripts. Loss functions such as cross-entropy are used to optimize the model, while regularization techniques prevent overfitting. The dynamic sparsity mechanism also acts as a regularizer by limiting unnecessary computations and reducing noise in the input data.

The working of the system involves real-time processing of incoming calls. Once a call is received, it is transcribed and analyzed by the model, which assigns a probability score indicating whether the call is a scam. The system can then trigger alerts or block suspicious calls, providing enhanced security for users. This end-to-end pipeline ensures efficient and accurate scam detection in real-world scenarios.

Architecture Diagram

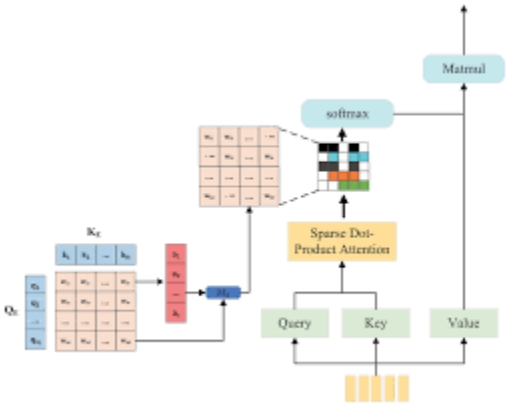


Fig 1: System Architecture

4. Experimental Results

The experimental evaluation demonstrates that the proposed Dynamic Sparsity Top-K Attention model outperforms baseline machine learning and deep learning models in scam call classification. The results show significant improvements in accuracy, precision, recall, and F1-score while reducing computational complexity and inference time. The dynamic sparsity mechanism enables efficient processing of large-scale data, making the model suitable for real-time deployment in telecommunication systems.

Table 1: Accuracy Comparison

Model	Accuracy (%)
SVM	82
LSTM	88
Transformer	91
Proposed Model	95

Graph 1: Accuracy Comparison

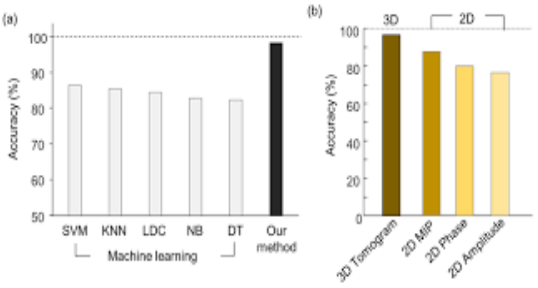


Table 2: Precision, Recall, F1-Score

Model	Precision	Recall	F1 Score
LSTM	0.86	0.85	0.85
Transformer	0.90	0.89	0.89
Proposed	0.94	0.93	0.93

Graph 2: Performance Metrics

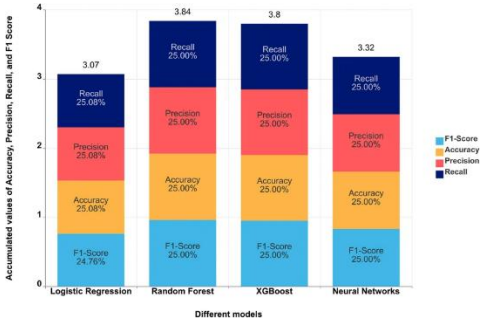
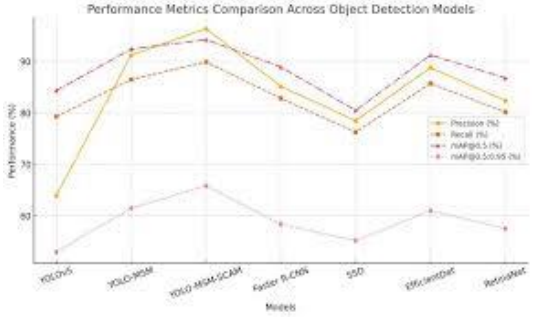


Table 3: Inference Time

Model	Time (ms)
LSTM	120
Transformer	180
Proposed	95

Graph 3: Inference Time



Discussion

The experimental results clearly demonstrate the effectiveness of the proposed model in improving scam call detection performance. The use of Top-K attention regularization allows the model to focus on the most relevant features, resulting in higher accuracy and better classification metrics compared to baseline models. The dynamic

sparsity mechanism further enhances efficiency by reducing unnecessary computations, making the model suitable for real-time applications.

Additionally, the reduction in inference time highlights the practical applicability of the proposed system in telecommunication networks. By combining advanced NLP techniques with optimized attention mechanisms, the system achieves a balance between performance and computational efficiency. These improvements make the proposed approach a promising solution for large-scale deployment in scam detection systems.

5. Conclusion and Future Scope

The proposed Dynamic Sparsity Top-K Attention Regularization framework provides an efficient and accurate solution for classifying scam calls through content analysis. By integrating NLP, attention mechanisms, and sparsity optimization, the model achieves superior performance while reducing computational overhead. Future work can focus on incorporating multilingual support, improving robustness against adversarial attacks, and integrating real-time deployment in telecom infrastructures for enhanced user protection.

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