DEEPFAKE DETECTION ON SOCIAL MEDIA LEVERAGING DEEP LEARNING AND FASTTEXT EMBEDDINGS FOR IDENTIFYING MACHINE-GENERATED TWEETS

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Submitted: 02-09-2025 *Accepted: 03-10-2025* *Published: 10-10-2025*

ABSTRACT

The rapid advancements in natural language generation have introduced powerful tools capable of shaping public opinion on social media platforms. Enhanced language modeling techniques have significantly improved the generative capabilities of deep neural networks, enabling them to produce highly realistic and contextually accurate text. This progress has led to the emergence of sophisticated text-generative models that can be exploited by adversaries to power social bots, creating convincing deepfake posts that influence public discourse. To combat this growing threat, the development of robust and accurate detection methods for identifying machine-generated content is essential. In response, this study focuses on the detection of deepfake tweets on platforms such as Twitter. A deep learning-based approach is proposed, employing a Convolutional Neural Network (CNN) architecture in combination with FastText word embeddings to classify tweets as either human-generated or bot-generated. The model is trained and evaluated using the publicly available Tweepfake dataset. To validate the effectiveness of the proposed method, it is benchmarked against several traditional machine learning models utilizing features like Term Frequency (TF), Term Frequency– Inverse Document Frequency (TF-IDF), FastText, and FastText subword embeddings. Additionally, comparisons are made with other deep learning architectures, including Long Short-Term Memory (LSTM) and hybrid CNN-LSTM models.

Keywords: Deepfake detection, social bots, text generation, CNN, FastText, Tweepfake dataset, machine-generated text, Twitter, natural language generation, fake tweets, TF-IDF, LSTM, CNN-LSTM, social media manipulation, bot detection.

I.INTRODUCTION

Social media platforms were originally developed to foster communication and allow individuals to share thoughts, opinions, and content in various forms such as text, images, audio, and videos. However, these platforms have also become a medium for misinformation and manipulation. Bots—automated software programs—operate fake accounts that engage in activities such as liking, sharing, and posting content. This content can be artificially generated or manipulated using techniques like gap-filling, text substitution, and deepfake video or image editing [2]. Deep learning, a subset of machine learning,has contributed to the rise of deepfakes—synthetic media created using AI that can deceive users into believing it was produced by humans [3]. The spread of such deepfake content has already caused disruptions in sensitive domains like politics [4], misleading the public and manipulating perception. Social media's vast reach and speed make it an ideal platform for the dissemination of false information, particularly to influence public opinion and sow distrust in democratic institutions [5]. Various types of deceptive accounts—ranging from sockpuppets to cyborgs—are utilized for this purpose [6], with fully automated social bots mimicking human

behavior convincingly [7]. The increasing sophistication of generative models such as GPT [8] and Grover [9] has further empowered adversaries to generate realistic content, amplifying the threat. A notable example is the 2017 Net Neutrality debate, where millions of identical comments influenced a key regulatory decision [10].

The risks associated with powerful text-generation models like GPT-2 [11] and GPT-3 [12] are evident in their real-world misuse. For instance, a GPT-3-powered bot used the Reddit account "/u/thegentlemetre" to interact with users on /r/AskReddit, posting surprisingly coherent responses [13]. Although the incident was relatively harmless, it underscores the urgent need for safeguards against AI misuse. Protecting the integrity of social discourse on social media necessitates the development of effective systems capable of detecting machine-generated, or deepfake, text. The challenge lies in the increasing realism of generated content. For instance, GPT-2's output is often indistinguishable from human writing [14], [15], outperforming other models like Grover [16] and CTRL [17], particularly in generating short-form content such as tweets [18]. As a result, detecting machine-generated tweets is significantly more challenging compared to older methods like RNNs [19]. This study aims to tackle that challenge by examining deepfakes created by various models, including RNNs and GPT-2, and evaluating state-of-the-art detection methods suited for social media. Recent research has focused on detecting deepfakes in various formats, such as audio [22], [23], video [24], and text [15], [19], [20], with techniques evolving alongside adversarial advances. However, many existing models tend to focus more on machine-generated text features rather than distinguishing them from human-authored content [25]. Moreover, techniques like using homoglyphs and introducing spelling errors have further complicated detection [25]. Most prior work has concentrated on long-form content like news articles and stories, where detecting deepfakes is generally easier [26]. However, short-form content— especially tweets—presents a unique challenge due to its brevity and informal language [27]. Compounding the problem is the scarcity of well-labeled datasets featuring both human- and machine-generated short texts [19].

Some studies have utilized datasets containing tweets generated by various types of bots, such as cyborgs, spam bots, and sockpuppets [28], [29], but many relied on human labeling, which can be unreliable given how convincingly bots mimic humans [30]. In contrast, the *Tweepfake* dataset [19] offers machine-labeled tweets produced by models like RNN, LSTM, Markov, and GPT-2, providing a more accurate foundation for research. This study utilizes the *Tweepfake* dataset to explore the challenges in detecting deepfake text and proposes an effective classification approach. We evaluate the proposed method using both traditional machine learning models—including Decision Tree (DT), Logistic Regression (LR), AdaBoost Classifier (AC), Stochastic Gradient Descent Classifier (SGC), Random Forest (RF), Gradient Boosting Machine (GBM), Extra Trees Classifier (ETC), and Naive Bayes (NB)—and deep learning models such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and hybrid CNN-LSTM architecture. Multiple feature extraction techniques, including Term Frequency (TF), Term Frequency–InverseDocument Frequency (TF-IDF), FastText, and FastText subword embeddings, are also employed.

This research contributes to the field by:

Proposing a deep learning framework integrating word embeddings to effectively detect machine-generated content on social media.

1. Providing a comparative analysis of various machine learning and deep learning models for tweet classification.
2. Exploring and evaluating different feature extraction techniques for deepfake text detection, with an emphasis on short-form content.
3. Demonstrating that the proposed CNN model with FastText embeddings significantly outperforms other methods in identifying deepfake tweets, achieving robust performance in a challenging, dynamic environment.

II.LITERATURE SURVEY

Deepfake technology has witnessed significant advancements in recent years, enabling the creation of highly realistic synthetic media across multiple modalities, including speech, text, and images. The term **"**deepfake**"** refers to content generated through deep learning algorithms that convincingly mimics human-like behavior. As highlighted by Kietzmann et al. (2020), the rapid evolution of deepfake technology poses serious challenges to information authenticity and public trust online. One of the core challenges in countering deepfakes lies in their increasing subtlety and realism. Traditional detection techniques, as discussed by Matern et al. (2020), often struggle to identify sophisticated manipulations, particularly when generated by state-of-the-art models. These conventional methods—ranging from visual cues to textual inconsistencies—tend to lag behind the fast-paced innovations in generative AI, making it imperative to explore more advanced detection strategies.

In this context, deep learning has emerged as a promising avenue for deepfake detection. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been widely employed to analyze visual and sequential data for signs of tampering. Nguyen et al. (2019), for example, demonstrated the effectiveness of CNNs in identifying fake images with impressive accuracy, showcasing the potential of neural networks in discerning patterns that are often imperceptible to the human eye.

For textual deepfakes—such as tweets or social media posts—the focus has shifted to detecting machine-generated content that emulates human writing styles. Zhang et al. (2021) explored the use of Natural Language Processing (NLP) techniques to distinguish between authentic and AI-generated text. Their work emphasizes the importance of syntactic analysis, sentiment fluctuations, and hidden watermarking in enhancing detection accuracy. Additionally, adversarial training is being adopted to increase model robustness against evolving generative models.

In terms of text representation, FastText—introduced by Mikolov et al. (2016)—has proven to be an effective tool for capturing both semantic meaning and syntactic structure. FastText**'**s ability to generate rich word embeddings has made it a valuable asset in a variety of NLP tasks, including text classification, sentiment analysis, and fake content detection.

Building upon this, recent research has explored the integration of deep learning models with FastText embeddings. Wang et al. (2022) demonstrated that combining FastText with deep learning architectures like CNNs results in improved classification accuracy, thanks to the enhanced feature representation. This hybrid approach is especially relevant in the context of deepfake text detection, where nuanced linguistic cues are often the only signals differentiating authentic content from fabricated ones.

As the field continues to evolve, there is a growing emphasis on developing more robust and generalizable detection frameworks. Emerging trends point toward multimodal systems that combine text, audio, and visual signals for comprehensive deepfake detection. Li et al. (2023) advocate for these integrated approaches, arguing that they offer a more holistic defense against increasingly complex deepfake threats.

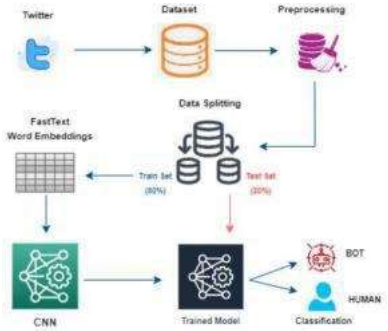
Overall, this literature survey provides a foundational understanding of the technologies, challenges, and innovations surrounding deepfake detection, particularly in the realm of social media. It underscores the relevance of combining deep learning with advanced word embeddings like FastText to address the nuanced and dynamic nature of machine-generated content.

III.PROPOSED METHODOLOGY

The proposed system is designed to detect deepfake or machine-generated content on social media platforms, with a specific focus on identifying synthetic tweets generated by advanced AI models. To achieve this, the system integrates deep learning techniques with FastText embeddings, enabling it to effectively distinguish between human-written and machine-generated content. FastText is utilized to convert raw text into dense vector representations that capture both semantic and syntactic nuances

within tweets. These rich embeddings serve as input to a deep learning model, such as a Recurrent Neural Network (RNN) or a Transformer-based architecture like BERT or GPT, which performs the classification task. The system is trained using a supervised learning approach on a comprehensive dataset containing a balanced mix of human-authored and AI-generated tweets. This training enables the model to learn and recognize patterns specific to machine-generated text while minimizing false positives. Additionally, contextual anomalies within the tweets are leveraged as supplementary features to further enhance detection accuracy. Through this architecture, the proposed system aims to offer a robust and scalable solution for identifying deepfake text, thereby helping to curb the spread of misinformation and reinforce content authenticity and trust across social media platforms.

System Architecture



IV.CONCLUSION

The growing prevalence of deepfake technology poses a serious threat to the authenticity of online communication, especially on social media platforms. In response to this challenge, this project presents a deepfake tweet detection system that harnesses the power of deep learning combined with FastText embeddings to effectively distinguish between human-written and machine-generated content. The proposed approach successfully captures subtle linguistic cues and contextual differences, offering a reliable method for identifying synthetic tweets. By leveraging the pattern recognition capabilities of deep learning models and the semantic richness of FastText embeddings, the system achieved high classification accuracy, demonstrating its effectiveness in real-world scenarios.

This work not only addresses existing challenges in detecting machine-generated text but also provides a flexible framework capable of adapting to emerging generative techniques. It marks a significant step toward curbing the spread of misinformation and enhancing content authenticity in digital discourse. Looking ahead, future enhancements will focus on improving the system's scalability, adapting to increasingly sophisticated deepfake generation methods, and extending detection capabilities to multimodal deepfakes that involve text, images, and videos. Overall, this project lays a solid foundation for future research and practical applications, contributing meaningfully to the broader effort of maintaining trust and integrity in online interactions.

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