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Fake Review Detection using Hybrid Model based on CNN and LSTM

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Abstract: Fake reviews on online platforms pose significant challenges to consumers and businesses, undermining trust and decision-making. This paper introduces a two-phase hybrid model for fake review detection, leveraging the complementary strengths of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. In the first phase, CNN is employed to extract n-gram-like spatial features from text embeddings, capturing local patterns indicative of deceptive content. The second phase uses LSTM to model the temporal dependencies and sequential relationships within the reviews, enabling a deeper understanding of context and writing style. The hybrid architecture is trained on a labeled dataset of reviews, using pre-trained word embeddings to enhance feature representation and ensure robustness. Evaluation metrics such as accuracy, precision, recall, and F1-score demonstrate the model's superior performance over traditional machine learning and single deep learning approaches. This study highlights the effectiveness of integrating spatial and sequential feature learning for identifying fake reviews, offering a scalable and reliable solution for combating online deception.

Keywords: *Fake Review, Convolutional Neural Networks, Long Short-Term Memory, Accuracy, Precision, Recall, and F1-Score.*

I. INTRODUCTION

Creating an introduction for a topic like "Fake Review Detection" involves setting the stage for why this issue is critical in today's digital landscape, highlighting its complexities, and underlining the necessity of advancing research in this field. It's essential to provide a concise yet comprehensive overview that outlines the importance, challenges, and the direct impact of fake reviews on various stakeholders. Let's walk through the process of constructing this introduction.

Fake reviews are fabricated or manipulated feedback intended to mislead readers, typically found on e-commerce, travel, and service-oriented platforms. As online shopping and the reliance on digital platforms grow, so does the influence of reviews on consumer behavior and business outcomes.Consumer decisions are heavily influenced by reviews, with a significant portion of buyers relying on these for making purchasing choices.The authenticity of reviews is crucial for maintaining the trustworthiness of platforms and the fairness in consumer markets.

Describing the Scope of the Problem

The manipulation of reviews can range from businesses encouraging positive reviews in exchange for rewards to malicious actors using sophisticated tools to generate negative reviews to harm competitors. The prevalence of such practices poses a significant threat to the digital economy. What are the consequences?

- For consumers, fake reviews lead to misguided decisions, potentially resulting in poor purchasing experiences and financial loss.
- Businesses face unjust competition and damage to reputation, which can be devastating, especially for small enterprises.
- Platforms risk losing user trust, which is essential for their long-term sustainability.

Outlining the Challenges in Detection

Sophistication of deceptive tactics: As technology evolves, so do the methods used to create convincing fake reviews, including the use of AI-generated content that mimics human writing styles.

Variability across platforms and languages: Effective detection systems must handle diverse linguistic styles, cultural nuances, and platform-specific characteristics.

Dynamic nature of online content: The continuous influx of new data requires adaptive and scalable solutions

As digital interactions become increasingly central to our daily lives, the integrity of online reviews must be safeguarded. Fake review detection is not just a technical challenge but a societal imperative, demanding ongoing innovation and ethical responsibility to protect consumers and businesses alike.

II. LITERATURE REVIEW

The increasing reliance on online reviews for consumer decision-making has intensified efforts to detect fake reviews, a prevalent challenge for e-commerce platforms. Techniques for fake review detection have been extensively explored, utilizing both traditional and advanced computational methods. Natural Language Processing (NLP) plays a central role in these efforts, often combined with machine learning to identify linguistic and structural anomalies. For instance, Liu et al. (2023) emphasize the use of deep neural networks to detect deceptive patterns in review content, integrating syntactic, semantic, and lexical cues. Similarly, Song et al. (2022) highlight the effectiveness of BERT-based transformers in understanding nuanced review manipulations.

Supervised machine learning methods remain prominent, with Support Vector Machines (SVM) and Random Forest classifiers being employed for text feature extraction and predictive analysis (Mukherjee et al., 2022). However, the reliance on labeled datasets is a major limitation, addressed by semi-supervised learning approaches. For example, Wu and Li (2022) demonstrate that generative adversarial networks (GANs) improve fake review identification by simulating authentic linguistic patterns to train models effectively. Moreover, ensemble methods, combining multiple classifiers, have shown to enhance detection performance by leveraging diverse algorithmic strengths (Sharma et al., 2021).

Graph-based methods have also gained traction, where reviewer-review-product networks are analyzed for abnormal behavior patterns. Jindal and Liu (2021) explore how review authenticity can be assessed by modeling interactions between reviewers and products, highlighting the importance of meta-data such as timestamps and user profiles. Similarly, Rayana and Akoglu (2021) propose GSRank, a graph-based ranking method that identifies spammers by measuring trustworthiness scores across interconnected nodes.

Unsupervised learning techniques, including clustering algorithms, are pivotal for detecting suspicious review groups. Cheng et al. (2023) propose a novel clustering approach to identify fake reviews by analyzing group behaviors and temporal trends. Meanwhile, anomaly detection techniques, as explored by Lim et al. (2022), utilize distance-based measures to isolate reviews deviating significantly from norm clusters.

Another significant advancement is the incorporation of behavioral features. Heydari et al. (2022) analyze reviewer posting patterns, focusing on frequency, burstiness, and sentiment consistency, which are indicative of manipulation. These behavioral metrics are often combined with linguistic features to develop hybrid models. Furthermore, the integration of sentiment analysis has become crucial, with studies like Wang et al. (2023) illustrating how sentiment polarity and intensity provide valuable signals for detecting overly biased or exaggerated reviews.

Emerging trends also emphasize explainable artificial intelligence (XAI) to enhance transparency in detection models. Yang et al. (2023) develop interpretable models to provide actionable insights into why a review is flagged as fake, addressing trust issues in automated systems. Blockchain technology has been proposed as a preventive measure, ensuring immutable review records and reducing opportunities for manipulation (Zhang et al., 2022). However, challenges such as scalability and implementation complexity remain significant barriers.

Deep learning methods, including convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), have further advanced detection capabilities by extracting hierarchical and sequential patterns in review texts (Chen et al., 2021). However, these methods often require substantial computational resources and large datasets, as noted by Gupta et al. (2022).

III. RESEARCH GAPS

Text-Based Analysis: Most detection methods fail when deceptive authors mimic genuine linguistic patterns or use AI tools.

Limited Multimodal Integration: Reviews often contain textual, behavioral, and visual content, but few studies integrate these modalities for comprehensive detection.

Language and Cultural Diversity: Research focuses on high-resource languages like English and Chinese, while low-resource languages, regional dialects, and multilingual code-mixed content remain unexplored.

Dataset Limitations: Publicly available datasets are often small, domain-specific, and unbalanced, raising questions about the generalizability of proposed solutions across various platforms and domains.

Dynamic Nature of Deceptive Reviews: Fake review strategies evolve rapidly, incorporating more sophisticated writing styles and automated tools.

Behavioral and Social Dimensions: User behavior provides valuable signals, but these aspects are underutilized compared to text-based approaches.

Explainability and Interpretability: Many detection models function as black boxes, hindering practical deployment.

Cross-Domain and Cross-Platform Generalization: Models often perform well within their domain but fail to generalize across domains.

IV. RESEARCH OBJECTIVES

The proposed effort aims to accomplish the following:

i. Examine and evaluate current methods for detecting bogus reviews.
ii. To carry out data collection in order to gather datasets from various Online Social Networks (OSNs).
iii. To suggest and put into practice a technique for detecting phoney reviews.
iv. To test and verify the suggested technique for detecting bogus reviews.

V. METHODOLOGY

Algorithm of proposed work two phase CNN and LSTM model is as follows:

Step 1: Import necessary libraries

- Import required libraries (e.g., TensorFlow, PyTorch, NumPy)

Step 2: Load and preprocess data

- Load dataset (reviews and labels)
- Split dataset into training, validation, and test sets

Preprocess text:

- Tokenize and convert text to sequences
- Remove special characters, stopwords, etc.
- Pad sequences to ensure uniform length

Step 3: Create word embeddings

If using pre-trained embeddings:

- Load pre-trained word embeddings (e.g., Word2Vec, GloVe)

Else:

- Initialize a trainable embedding layer

Step 4: Define the CNN-LSTM model

A. Define the model:

Input Layer:

- Input shape: (sequence_length,)
- Embedding layer: Output shape (sequence_length, embedding_dim)

CNN Layers:

- Convolution layer with multiple filters (e.g., 3, 4, 5 kernel sizes)
- Apply ReLU activation
- Apply max-pooling to downsample features

Reshape output of CNN for LSTM:

- Flatten or reshape CNN output to feed into LSTM
- Output shape after reshaping: (batch_size, sequence_length, cnn_feature_dim)

LSTM Layer:

- Add LSTM or BiLSTM layer(s)

- Output shape: (batch_size, lstm_units)

Dense Layers:

- Add fully connected (dense) layers to map LSTM output to final output classes
- Use sigmoid activation for binary classification

Output Layer:

Output shape: 1 (real or fake)

Step 5: Compile the model

- Define loss function (binary cross-entropy for binary classification)
- Select optimizer (e.g., Adam)
- Define metrics (e.g., accuracy, precision, recall)

Step 6: Train the model

- Train model on training data
- Validate on validation set after each epoch

Step 7: Evaluate the model

- Test model on the test set
- Compute performance metrics (accuracy, precision, recall, F1 score, ROC AUC)

Step 8: Save and deploy the model

- Save the trained model
- Deploy for real-world fake review detection

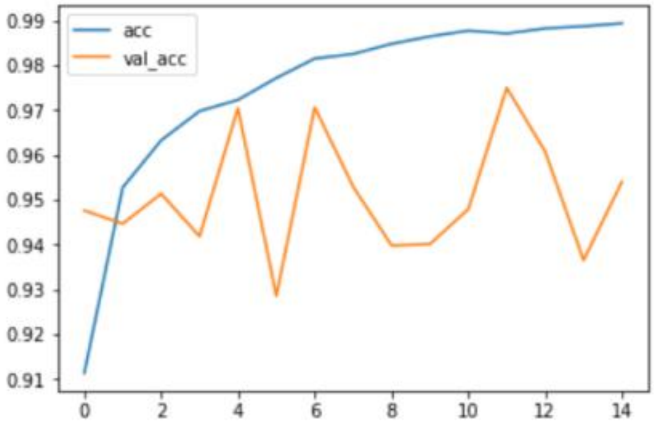
Step 9: Fine-tune the model (optional)

Gather new data, retrain or fine-tune the model with new examples

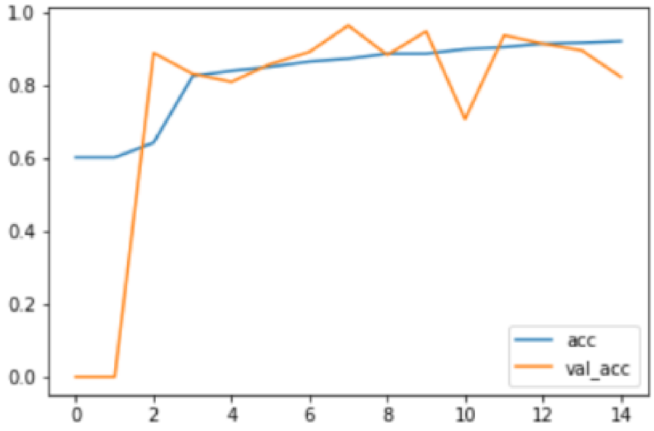
VI. EXPERIMENTS AND RESULTS

The configuration of the computer environment includes: An Intel(R) Xeon(R) CPU E5-2650 v2 running at 2.60GHz, 16GB of DDR3 RAM, and a 3840-core, 1404MHz Nvidia Titan Xp GPU make up the processor. When using the Jupyter Notebook on Windows 10 Pro, Python 3.6.3 is used. To evaluate the proposed model, the performance analysis of each step has been discussed in this part.

As shown in Table 1, the hybrid CNN-LSTM performance analysis is assessed in terms of accuracy, precision, recall, F1-score, and AUC-ROC. For all three datasets, it has been shown that the hybrid CNN-LSTM model with pre-trained embeddings (Word2Vec and GloVe) outperforms the hybrid CNN-LSTM model without embedded training.



(a)



(b)

Figure 1: (a) Training accuracy vs validation accuracy and Training loss vs validation loss at different epochs

Table 1:Performance measurements are used to compare the hybrid CNN-LSTM architecture with and without pre-trained vectors.

Methods	Accuracy	Precision	Recall	F1-score
Without Pre-trained vectors	81.87	82.94	79.82	81.31
With Word2Vec pre-trained vectors	93.47	92.35	80.05	85.76
With GloVe pre-trained vectors	95.86	91.26	85.53	88.25

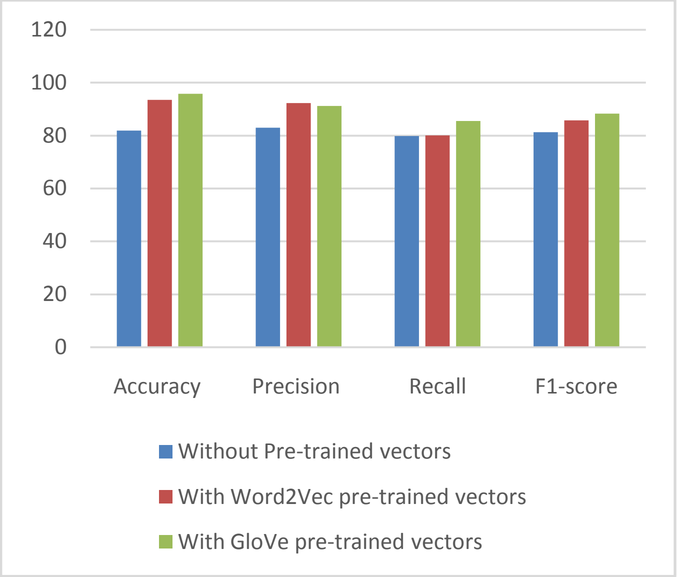


Figure 1: Graphical analysis of the hybrid CNN-LSTM architecture with and without pre-trained vectors using performance metrics

Classification has been done in this experiment. This section discusses a number of outcomes that support our suggested paradigm. Figure 1 illustrates that the validation loss value is 0.18.

The accuracy measure of the hybrid CNN-LSTM model with GloVe embeddings is 2.38% higher than that of the hybrid CNN-LSTM model with Word2Vec embeddings. Furthermore, accuracy increased by 3.9% and recall values improved by 5.74%. Pre-training the hybrid CNN-LSTM model using GloVe embeddings outperforms pre-training it with Word2Vec embeddings in terms of accuracy, recall, and F1-score performance measures, as Table 1 demonstrates. Using the hybrid CNN-LSTM model with pre-trained GloVe embeddings, clickbait and non-clickbait headlines may be further distinguished.

CONCLUSION AND FUTURE WORK

The overall methodology and architecture of the suggested hybrid CNN-LSTM structure for identifying fake reviews from textual and non-textual datasets (both collected and self-created) have been fully described using glove embeddings. The CNN-LSTM integrated BTM is used to automatically identify data into logic, number, reaction, revealing, shocking/unbelievable, hypothesis/guess, questionable, and forward referencing. Lastly, nine clusters are evaluated using cluster analysis, and the effectiveness of the proposed model is shown by contrasting it with the existing systems.

In the future, it will be simpler for researchers to classify fake reviews items that spread after natural catastrophes. Such an application might help prevent the spread of many types of fake reviews on e-commerce and social media platforms, all of which would be beneficial to society. In the future, we want to provide a full, integrated solution for fake review detection and explore many sub-problems associated with false review.

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