Enhancing Social Media Integrity: A Machine Learning-Based Rumor Identification System Utilizing CNN for Accurate Real-Time Tweets

Introduction

In today's digital age, social media platforms are not just channels for social interaction but also battlefields for information integrity. The Enhancing Social Media Integrity project introduces a machine learning-based rumor identification system that utilizes convolutional neural networks (CNN) to classify tweets in real-time. This initiative seeks to automate the detection of rumors, providing a robust solution to maintain the reliability of information circulating on social media.

Literature Review

S.No	PAPER TITLE	YEAR	AUTHOR	Challenges	OVERVIEW	Merits	Demerits
1	A Novel Node-Level Rumor Propagation Model with Recommendation Mechanism	2019	H. Peng and X. Yang	Propagation speed, recommendation accuracy	Proposes a node-level model with a recommendation mechanism to manage rumor propagation	Enhanced rumor management	Limited to specific network structures
2	A rumor source identification method based on node embeddings and community detection in social networks	2023	W. Liu, C. Xie and S. Zong	Accurate source identification	Utilizes node embeddings and community detection for rumor source identification	Improved source identification accuracy	High computational cost
3	Rumor Propagation Control With Anti-Rumor Mechanism and Intermittent Control Strategies	2024	X. Zhong, Y. Yang, F. Deng and G. Liu	Controlling propagation effectively	Introduces anti-rumor mechanisms and intermittent control strategies	Effective propagation control	Implementation complexity

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4	A Multi-Model Intelligent Approach for Rumor Detection in Social Networks	2022	N. M. Santhosh, J. Cheriyan and L. S. Nair	Integration of multiple models	Combines several models for improved rumor detection	Increased detection accuracy	Resource-intensive
5	SIRQU: Dynamic Quarantine Defense Model for Online Rumor Propagation Control	2022	Z. Liu, T. Qin, Q. Sun, S. Li, H. H. Song and Z. Chen	Dynamic quarantine management	Proposes a dynamic quarantine model for controlling rumor spread	Effective rumor control	Requires constant monitoring
6	Computational Rumor Detection Without Non-Rumor: A One-Class Classification Approach	2019	A. Ebrahimi Fard, M. Mohammadi, Y. Chen and B. Van de Walle	Lack of non-rumor data	Uses one-class classification for rumor detection	Works without non-rumor data	May miss subtle rumors

S.No	PAPER TITLE	YEAR	AUTHOR	Challenges	OVERVIEW	Merits	Demerits
7	Rumour Source Identification in Static Network	2020	S. Maheswari and V. Malik	Static network limitations	Focuses on identifying the rumor source in static networks	Effective for static networks	Not suitable for dynamic networks
8	Dynamic Semantic Analysis for Rumor Detection (DSARD): A suggestion	2024	F. Mohammadi, M. Keyvanpour and B. Masoumi	Dynamic analysis challenges	Suggests a dynamic semantic analysis approach for rumor detection	Adapts to new data	Complex implementation
9	Arabic Rumor Detection Using Contextual Deep Bidirectional Language Modeling	2022	N. O. Bahurmuz, G. A. Amoudi, F. A. Baothman, A. T. Jamal, H. S. Alghamdi and A. M. Alhothali	Language-specific issues	Utilizes deep bidirectional language modeling for Arabic rumor detection	Accurate for Arabic content	Language limitations

S.No	PAPER TITLE	YEAR	AUTHOR	Challenges	OVERVIEW	Merits	Demerits
10	Scientific Rumors Detection in Short Online Texts	2021	H. Zeng, R. Wang, Y. Huang, X. Cui and Q. Jiang	Short text complexity	Focuses on detecting scientific rumors in short texts	Effective for short texts	Limited to scientific content
11	A hybrid deep learning model based on CNN-BiLSTM for rumor detection	2021	N. Rani, P. Das and A. K. Bhardwaj	Model complexity	Combines CNN and BiLSTM for improved detection	High accuracy	Computationally expensive
12	Research on Micro-blog Rumor Recognition Based on Machine Learning	2021	L. Chen	Micro-blog specific challenges	Applies machine learning to micro-blog rumor detection	Adaptable to micro-blogs	Limited to specific platforms

S.No	PAPER TITLE	YEAR	AUTHOR	Challenges	OVERVIEW	Merits	Demerits
13	An Implicit Crowdsourcing Approach to Rumor Identification in Online Social Networks	2020	A. Osho, C. Waters and G. Amariucai	Crowdsourcing reliability	Uses implicit crowdsourcing for rumor identification	Leveraging crowdsourcing	Potential biases
14	Rumor Source Detection on Interconnected Social Networks	2022	A. Khan, M. F. Shaikh, F. Sherwani, S. H. Hassan and A. Kalifa Soluman Ahteewash	Interconnected network complexity	Focuses on source detection across interconnected networks	Effective for interconnected networks	High complexity
15	Role of Various Features in Identification of Rumors in the Social Network	2021	S. Shelke and V. Attar	Feature selection challenges	Analyzes various features for rumor identification	Comprehensive feature analysis	Feature dependence

Problem Statement

Traditional approaches to rumor detection on social media are largely manual and keyword-based, leading to delays and inaccuracies in identifying misinformation. These methods struggle to keep pace with the rapid spread of content and fail to contextualize the nuances of language, often resulting in the misclassification of information. There exists a crucial need for an automated system that can efficiently and accurately process the veracity of vast amounts of data in real time.

Motivation

- Rising Misinformation: The exponential increase in online misinformation poses serious social and political risks.
- Public Trust: Accurate information dissemination is key to maintaining public trust in digital platforms.
- Resource Efficiency: Automating rumor detection frees up significant human resources for more complex analytical tasks.
- Scalability: An automated system can scale to handle the growing volume of data on social media platforms effectively.

Objectives

- To develop a machine learning model that classifies tweets as rumors or non-rumors with high precision.
- To implement advanced text preprocessing techniques to enhance the accuracy of the classification.
- To provide a real-time predictive system using a user-friendly interface for easy access and interaction.
- To utilize CNN for deep learning analysis to capture and understand the contextual nuances of tweet data.
- To integrate the system seamlessly with existing social media platforms to provide immediate benefits.

Scope

- Model Application: Capable of processing and classifying diverse tweet data accurately.
- User Accessibility: System designed with an intuitive interface for user interaction and feedback.
- Impact Potential: Ability to significantly reduce the spread of misinformation.
- Adaptability: Designed to evolve with changing social media dynamics and data types.

Feasibility

Technical Feasibility:

- Supported by advanced machine learning libraries and frameworks such as TensorFlow and Keras, ensuring robust model development and deployment.

Economic Feasibility:

- Cost-effective as it leverages existing open-source technologies and minimal operational costs post-deployment.

Operational Feasibility:

- Can be integrated into current social media infrastructures with minimal disruption and supports scalable deployment across various platforms.

Tools used

- **Programming Languages:** Python
- **Libraries:**
  - **TensorFlow:** For building and training the deep learning model.
  - **Keras:** Simplifies the creation of neural networks.
  - **Streamlit:** To develop the user interface.
  - **NLTK:** For natural language processing tasks.
  - **NumPy:** For numerical operations on data.
- **Development Environment:** Jupyter Notebook, VSCode

Dataset

PHEME Dataset for Rumour Detection and Veracity Classification: The dataset is based on the renowned PHEME dataset, which is designed specifically for the study of rumor detection and veracity classification on Twitter during critical breaking news events. This dataset includes over 60,000 tweets related to two significant events: the Germanwings crash and the Charlie Hebdo shooting.

Details of the Dataset:

- **Format**: The dataset is available in CSV format, making it accessible and easy to manipulate using common data processing tools.
- **Scope**: It focuses on tweets concerning only two of the several events covered by the original PHEME dataset, providing a concentrated view of rumor dynamics in these contexts.
- **Content**: This dataset categorizes tweets into rumors and non-rumors, offering a substantial volume of data for training machine learning models.
- **Utility**: Ideal for researchers and practitioners starting in the field of information classification, as it provides a rich source of real-world data for developing and testing rumor detection algorithms.
- **Data Quality**: Some entries contain null values, necessitating preprocessing steps such as cleaning and imputation to prepare the data for effective analysis.

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