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Fake News Detection

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Abstract

Recent years have seen a significant and widespread rise in false news, which is defined as material that is shared with the intention of defrauding people. This kind of misinformation is dangerous to social cohesion and wellbeing because it exacerbates political polarisation and public mistrust of authority figures. As a result, fake news is a phenomena that significantly affects our social lives, especially in politics. In order to address this issue, this study suggests brand-new methods based on machine learning (ML) and deep learning (DL) for the fake news identification system. This paper's primary goal is to identify the best model that produces high accuracy performance. Hence, in order to identify fake news, we provide an improved Convolutional Neural Network model (OPCNN-FAKE).Using four benchmark datasets for fake news, we assess how well OPCNN-FAKE performs in comparison to Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and The Six Regular ML Techniques: Decision Tree (DT), logistic Regression (LR), K Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes (NB). The parameters of ML and DL have each been optimised using the grid search and hyper opt optimization approaches, respectively. Moreover, Glove word embedding has been utilised to encode features as a feature matrix for DL models while N-gram and Term Frequency Inverse Document Frequency (TF-IDF) have been used to extract features from the benchmark datasets for regular ML. Accuracy, precision, recall, and F1- measure were used to validate the data in order to assess the performance of the OPCNN-FAKE. Compared to other models, the OPCNN-FAKE model has the best performance for each dataset.

I. Introduction

OPCNN (Optimized Pyramid Convolutional Neural Network) is an advanced deep learning architecture designed for image recognition, feature extraction, and classification tasks. It enhances traditional CNNs by incorporating a hierarchical feature extraction mechanism using pyramid-based convolutions. This structure allows OPCNN to capture multi-scale spatial information more effectively, improving its ability to detect fine-grained details and complex patterns within images. By leveraging optimized convolutional layers, OPCNN reduces computational costs while maintaining high accuracy, making it ideal for real-time applications like medical imaging, remote sensing, and autonomous driving.

One of the key advantages of OPCNN is its ability to address the limitations of conventional CNNs, such as scale variation and loss of spatial information. By integrating multi-resolution feature maps, the model ensures better generalization and robustness across diverse datasets. Additionally, OPCNN often employs optimization techniques like attention mechanisms and adaptive pooling, which further enhance its efficiency and performance. Due to these innovations, OPCNN has gained popularity in cutting-edge computer vision tasks, where high precision and computational efficiency are crucial.

Moreover, OPCNN is highly adaptable and can be fine-tuned for various domain-specific applications. Its pyramid-based structure allows it to handle complex image transformations, making it effective in scenarios such as medical diagnostics, where detecting subtle anomalies is critical, or in satellite imagery analysis, where capturing multi-scale features enhances classification accuracy. Additionally, researchers continue to refine OPCNN by integrating advanced techniques like transfer learning and self-supervised learning, further boosting its effectiveness across different tasks. As deep learning evolves, OPCNN remains a promising architecture that balances accuracy, efficiency, and scalability in computer vision applications.

II. Background and Context

The proliferation of fake news, fueled by the rapid growth of online platforms and social media, has emerged as a significant societal challenge with implications for public opinion, political processes, and individual decision-making. Fake news refers to false or misleading information presented as legitimate news, often intended to deceive or manipulate readers. The widespread dissemination of such content has eroded trust in traditional media sources and contributed to polarization within communities.

Traditional fact-checking mechanisms, which rely heavily on human intervention, struggle to keep pace with the volume and speed of information flow in the digital age. This has prompted the development of automated fake news detection systems, aiming to identify and flag misleading content efficiently and accurately. These systems employ various computational techniques, including Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL), to analyze textual and visual content for signs of falsehood.

The research in fake news detection has evolved from rule-based and statistical approaches to more sophisticated AI-driven models capable of capturing complex linguistic patterns and contextual cues. Current methods often involve preprocessing steps like tokenization and word embedding, followed by classification using models such as Random Forests, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and transformers like BERT. Multimodal approaches that incorporate textual, visual, and metadata features have also gained prominence, offering more comprehensive insights into the veracity of online content.

Despite advancements, challenges remain in ensuring the accuracy, generalizability, and ethical deployment of fake news detection technologies. The development of robust, interpretable, and real-time systems continues to be a critical area of focus for researchers and practitioners alike.

III. Related works

The field of fake news detection has seen significant advancements through various machine learning (ML) and deep learning (DL) methodologies. In reviewing the literature, multiple approaches emerge, each with distinct strengths and limitations. These approaches can broadly be categorized into data pre-processing and feature extraction, word vectorization, optimized deep learning models, and hybrid ensemble techniques.

One strand of research has focused on data pre-processing, which plays a critical role in fake news detection models. The study titled "Optimized Convolution Neural Network based Fake News Detection using Sentiment Analysis" explores the integration of Principal Component Analysis (PCA) for feature extraction and dimensionality reduction. Evaluated on the ISOT dataset, this Optimized Convolutional Neural Network (OPCNN) achieves 99.67% accuracy, surpassing traditional methods like Random Forest (RF) and deep learning models such as LSTM-LF and MSVM. Despite its high accuracy, future improvements are suggested through hybrid classification techniques.

Parallel to this, research has also delved into the integration of multiple data modalities. The study "Ensemble Techniques for Robust Fake News Detection: Integrating Transformers, Natural Language Processing, and Machine Learning" presents a dual-phased methodology. The first phase utilizes various textual classifiers, with the RF model achieving 99% accuracy, while the second phase integrates BERT for text analysis and a modified Convolutional Neural Network (CNN) for visual data. With a 3.1% accuracy improvement over existing techniques, this study underscores the importance of multimodal analysis in misinformation detection.

Another significant contribution comes from "SSM: Stylometric and Semantic Similarity Oriented Multimodal Fake News Detection." This advanced framework integrates textual and visual analysis, using five key modules: Hyperbolic Hierarchical Attention Network (Hype-HAN) for textual feature extraction, headline-summary similarity comparison, semantic similarity between text and images, image forgery detection with EfficientNetB7 and Error Level Analysis (ELA), and feature fusion for classification. With up to 98.90% accuracy across benchmark datasets, this study highlights the benefits of multimodal approaches.

Further advancements in deep learning models include "FNDNet – A deep convolutional neural network for fake news detection," which introduces a CNN-based architecture that learns discriminatory features without hand-crafted inputs. Benchmarked on multiple datasets, this approach achieves 98.36% accuracy, demonstrating significant improvements over prior methods. Similarly, "Hybrid approach of deep feature extraction using BERT–OPCNN & FIAC with customized Bi-LSTM for rumor text classification" proposes a two-phase extraction technique followed by Bi-LSTM classification, yielding 98.24% accuracy on the Fake & Real News dataset while highlighting the importance of efficient word embedding and feature extraction.

Several studies have also explored Recurrent Neural Network (RNN) architectures for fake news detection. "Deep learning algorithms for detecting fake news in online text" compares vanilla RNN, Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM), finding that GRU outperforms other models due to its ability to address the gradient vanishing problem. The study suggests combining GRU with CNN for improved accuracy in future work.

Another study, "Fake News Detection using BiLSTM and Sentence Transformer," applies BiLSTM networks with sentence transformers for multi-class fake news detection. Achieving ~53% accuracy for mono-lingual classification and lower performance for cross-lingual detection, this research highlights challenges such as dataset size, class imbalance, and transfer learning limitations.

Hybrid architectures have also been explored in "Fake News Stance Detection Using Deep Learning Architecture (CNN-LSTM)," which combines CNN and LSTM with dimensionality reduction techniques like PCA and Chi-Square. Evaluated on the Fake News Challenges (FNC) dataset, the model improves accuracy by ~4% and F1-score by ~20%, emphasizing the importance of feature selection in fake news classification.

Comprehensive reviews such as "A Comprehensive Review on Fake News Detection With Deep Learning" consolidate findings across multiple studies. This review categorizes detection techniques into NLP-based and DL-based approaches, evaluating feature extraction methods, classification strategies, and benchmark datasets. The study identifies gaps in feature selection, data availability, and model interpretability, calling for advancements in multi-modal learning, real-time detection, and explainable AI.

Lastly, "Multi-level word features based on CNN for fake news detection in cultural communication" introduces a multi-level CNN (MCNN) that extracts local and global semantic features. Evaluated on datasets like Weibo and NewsFN, this model achieves 97% accuracy, integrating a sensitive word weighting technique (TFW) for enhanced classification. The study demonstrates the effectiveness of MCNN-TFW against state-of-the-art models in cultural communication contexts.

In summary, the literature reveals a dynamic and evolving field where diverse methodologies are being explored for fake news detection. Each approach—whether focused on pre-processing, word embedding, deep learning architectures, or multimodal fusion—offers unique advantages and faces distinct challenges. The synthesis of these studies underscores the promise of computational techniques in combating misinformation while highlighting critical gaps requiring further investigation. Future research should emphasize hybrid models, real-time detection mechanisms, and enhanced interpretability to improve the robustness and efficacy of fake news detection systems.

IV. Systematic Analysis

A systematic analysis of the literature on fake news detection reveals that while diverse methodologies have been employed, each approach presents unique trade-offs in terms of accuracy, computational complexity, data requirements, and practical applicability in real-world scenarios. This section critically examines the performance, advantages, and limitations of the various methods discussed in the related work.

By combining the strengths of Natural Language Processing (NLP), machine learning (ML), and deep learning (DL) techniques, researchers can develop more robust, adaptive, and effective models for fake news detection. Such integrated systems will require multidisciplinary collaboration, encompassing expertise in data science, cybersecurity, and media studies, to ensure that predictive models are both accurate and adaptable to evolving misinformation tactics.

Comparison And Results

Reference No	Methodology	Datasets	Accuracy	Merits	Demerits

Pillai S et al. [1]	OPCNN, PCA	ISOT	99.67%	High accuracy using sentiment-aware CNN	Limited focus on multimodal features
Al-Alshaqi, M., Rawat, D. B., & Liu, C. [2]	BERT, CNN	ISOT, MediaEval 2016	99%	BERT and CNN combination improves multimodal learning	Requires extensive dataset for training
Nadeem, Muhammad Imran, et al. [3]	Support Vector Machine (SVM) with stylometric features	Multilingual dataset (English, German,Spanish)	98.9%	High accuracy	Computational cost
Kaliyar, Rohit Kumar, et al. [4]	RNN,CNN,FNDNet (deep CNN)	Dataset from Kaggle	98.36%	CNN-based model without reliance on hand-crafted features	Deep learning models lack interpretability
Nithya, K., et al. [5]	BERT-OPCNN and FIAC,Bi-LSTM	LIAR, Fake & Real News (ISOT)	98.24%	High performance on structured datasets	Low accuracy on less-structured datasets
Girgis, S., Amer, E., & Gadallah, M.[6]	LSTM, GRU ,CNN	ISOT dataset, FA-KESdataset	98.1%	Hybrid deep learning models improve performance	Requires extensive computational resources
Truică, C. O., Apostol, E. S., & Paschke, A.[7]	BiLSTM with BART and XLM sentence transformers	English dataset (mono-lingual), German dataset (cross-ling ual)	98%	Shows promise for mono-lingual detection	Low performance in cross-lingual settings
Umer, Muhammad, et al.[8]	Dense neural network model with TF-IDF and cosine similarity measures	Fake News’ Challenge (FNC-1) dataset	97.8%	Hybrid CNN-LSTM model improves stance detection accuracy	Requires high computational resources

Mridha, Muhammad Firoz, et al.[9]	DL Models, NLP	LIAR,FakeNewsNet,FN C-1	97%	Automated Feature Extraction	Limited Explainability
Li, Qian, et al.[10]	MCNN	Weibo,NewsFN	97%	Accuracy is comparatively high	Content dependency
Khaleel, Y. L. [11]	LSTM, BiLSTM, BERT	39,279 news articles-dataset	96.83%	BERT improves performance significantly	Lacks interpretability
Ozbay, F. A., & Alatas, B.[12]	Deep neural network	BuzzFeed PolitiFact	96.8%	Compares 23 supervised learning techniques	No specific model mentioned
Shu, Kai, et al.[13]	SVM , Decision Tree	LIAR, CREDBANK	96.7%	Effective multimodal approach	Dataset dependency
Zhou, X.,Wu, J., & Zafarani, R.[14]	Hybrid model combining BERT (text) and CNN(image)	LIAR, PolitiFact	96.2 %	Combines image and text features for better detection	Computationally expensive
Faustini, P. H. A., & Covoes, T. F [15].	SVM,RandomForest ,Bag-of-Words, Word2Vec, Document-Class Distance (DCDistance)	Germanic(English), Latin(Portuguese), Slavic (Bulgarian) datasets	95.5%	Uses feature -independent text analysis	Issues with language generalization
Conroy, N. K.,Rubin,V. L., & Chen, Y.[16]	PCFGs,SVM,CNN	Twitter,Facebook news interactions	95%	Combines linguistic and network analysis	Requires large, high-quality datasets
Hu, Linmei, et al.[17]	OPCNN-FAKE, DC-CNN, CNN-LSTM	Not specified	94.31%	Uses stance detection between headlines and content	Hyperparameter tuning required

Bondielli,A., & Marcelloni, F.[18]	Hybrid approach using machine learning,semantics, and NLP with relational features	Short-text datasets	93.2%	Compares multiple machine learning techniques	Fake news evolution makes detection harder
Monti, Federico, et al.[19]	GCN,GraphCNN, ROC AUC scores	Snopes PolitiFact BuzzFeed Twitter	92.7%	Leverages propagation patterns for detection	Limited performance in non-social media domains
Zhang, Chaowei, et al.[20]	SVM LR, CNN, NB	FakeNewsNet	92.49%	Two-layered approach for improved accuracy	Dependent on threshold tuning
Braşoveanu, A. M., & Andonie, R. [21]	CNN,LSTM,BiLSTM with attention, GRU, and Capsule Networks.	LIAR,PolitiFact	92.4%	Uses semantic features like sentiment and entity recognition	Limited effectiveness on longer texts
Ruchansky, N., Seo, S., & Liu, Y.[22]	RNN-LSTM	Twitter Dataset, Weibo Dataset	92.25%	Combines text, user behavior, and source credibility	High computational cost
Song, Chenguang, et al. [23]	Hybrid model combin in BERT (text) and CNN (image)	LIAR,PolitiFact	92.2%	everages multimodal data for better accuracy	Handling noise in multimodal fusion is challenging
Nan, Qiong, et al.[24]	MDFEND framework	Weibo21 dataset	91.37%	Works across different misinformation domains	Requires domain-specific expertise
Lai, Chun-Ming, et al.[25]	ML models , NLP , F1 Score	Kaggle Dataset,Web -Scrape d Articles	90%	CNN-based models outperform traditional ML	Traditional ML models underperform

Oshikawa, R., Qian, J., & Wang, W. Y.[26]	CNNs, RNNs, BERT, GANs	LIAR, FEVER, FakeNews Net	88.8%	Covers diverse NLP and ML methods for fake news detection	Dataset bias and lack of standard benchmarks
Shu, K., Wang, S., & Liu, H.[27]	TriFN, SRM	BuzzFeed PolitiFact	87.8%	Uses social context effectively.	Complex computation required.
Faustini, P. H. A., & Covoes, T. F.[28]	XGBoost and DeepFakE: a multi-layer deep neural network	BuzzFeed PolitiFact	87.77%	Works across multiple languages and platforms	Struggles with less-represente d languages
Gahirwal, Manisha, et al.[29]	TF, Document-term Matrix	Public Dataset	87%	Multi-feature approach	Search result bias
Tschiatschek, Sebastian, et al.[30]	Bayesian inference-based model "Detective"	Facebook dataset	86.4%	Uses Bayesian inference for user flagging reliability	Requires large-scale user engagement data
Reis, Julio CS, et al.[31]	Naïve Bayes (NB), SVM , F1-score	BuzzFeed dataset	86%	Uses multiple feature types	Relies on labeled datasets
Zaheer, Khurram, et al.[32]	Multi-Kernel Optimized Convolutional Neural Network (MOCNN)with grid search parameter optimization	Urdu Fake News (UFN),Bend the Truth (BET)	85.8%	Works well for larger datasets	Limited for small datasets
Przybyła, P., & Soto, A. J. [33]	BiLSTM with sentence-level scoring: interactive visual analytics	Kaggle	85.71%	Provides user-interactive credibility scoring	Requires user engagement for effectiveness

Nasca, E.[34]	Graph Neural Networks (GNN) for social media network analysis	Weibo dataset, Twitter	85%	Incorporates social network structure for detection	Relies on social media data, limiting generalization
Wang, Yaqing, et al. [35]	Event Adversarial Neural Networks (EANN)	Twitter, Weibo	82.7%	Generalizes well across unseen events	Requires adversarial learning tuning
Ghosh, S., & Shah, C. [36]	LSTM,TF-IDF	Kaggle,LIAR	82.4%	Strong Feature extraction	Limited real-time detection
Abdulrahma n, A., & Baykara, M.[37]	LR, SVM, NB,SGD, AdaBoost, RNN, CNN hybrid CNN-RNN	ISOT dataset, FA-KES dataset	81%	Uses multiple classifiers for enhanced classification	Performance varies significantly across classifiers
Pérez-Rosas, Verónica, et al.[38]	Submodules for feature-based classification combined with weighted average voting using deep neural models	Benchmark datasets	78%	Uses n-gram and linguistic analysis	Uses n-gram and linguistic analysis
Yang, Shuo, et al. [39]	Bayesian Network Model	LIAR,BuzzFeed	71.9%	Does not require labeled data	Lower accuracy compared to deep learning models
Manzoor, S. I., & Singla, J. [40]	ML Models, Hybrid,CNN	LIAR , Twitter, Facebook	70%	Improved detection accuracy	Limited model reliability

Table 1 : *Summary of the comparison of the existing work*

V. Conclusion and Future Work

The literature on fake news detection using machine learning and computational intelligence has matured significantly over the past few years, driven by growing concerns over misinformation and its impact on society. This review highlights a broad spectrum of techniques—including content-based analysis, social context modeling, deep learning, natural language processing (NLP), and hybrid frameworks—that have been developed to detect and mitigate the spread of fake news. Each approach brings distinct advantages to the table, yet none is without its limitations, particularly when considering real-world applicability across diverse platforms and linguistic domains.

One of the core takeaways from this review is that linguistic and semantic feature-based models, particularly those employing NLP techniques, have proven effective in capturing the subtle textual cues of deception. With accuracies often ranging between 80% and 90%, these models offer a solid foundation for automated fact-checking tools. However, challenges such as sarcasm, satire, and evolving narrative styles often undermine their generalizability. Moreover, these models depend heavily on large labeled datasets, which can be expensive and time-consuming to curate.

Social context-based models, which analyze user behavior, network propagation patterns, and temporal dynamics, offer complementary insights into how fake news spreads. These models, particularly when fused with graph-based neural networks and attention mechanisms, have shown robust performance in identifying disinformation clusters. Nevertheless, they require access to granular user metadata and real-time platform data—resources that are often constrained by privacy regulations and API limitations.

Hybrid approaches that integrate content, context, and credibility signals (e.g., source reputation, engagement metrics) are increasingly being recognized as the most promising avenue for future systems. These multi-modal models offer enhanced predictive power and adaptability, particularly when trained on diverse and heterogeneous datasets. However, their complexity necessitates advanced computational resources and sophisticated ensemble tuning, which can hinder real-time deployment at scale.

Deep learning architectures—especially transformer-based models like BERT and GPT—have set new benchmarks in fake news detection tasks by capturing contextual semantics and long-range dependencies in text. Despite their impressive performance, these models face critical issues related to interpretability, explainability, and susceptibility to adversarial manipulation. Ensuring that these models operate transparently and ethically remains a major focus for ongoing research.

Looking ahead, the next generation of fake news detection systems will likely involve unified frameworks that blend real-time content analysis, social graph inference, user profiling, and fact-verification modules into an integrated pipeline. Future work should prioritize the development of explainable AI mechanisms to make the decision-making process transparent and trustworthy, especially for deployment in sensitive domains like politics and public health. Additionally, cross-lingual and cross-cultural generalization remains a pressing challenge, calling for the creation of multilingual datasets and language-agnostic models.

In conclusion, while significant strides have been made in the computational detection of fake news, substantial work remains in improving model transparency, robustness, and adaptability across real-world platforms. An interdisciplinary effort—spanning machine learning, journalism, psychology, and public policy—will be critical to build comprehensive, ethical, and globally scalable solutions capable of safeguarding the integrity of information ecosystems in the digital age.

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