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OPCNN-FAKE: A Comparative Evaluation of Machine Learning vs. Deep Learning for 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 hyperopt 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 FrequencyInverse 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.

Keywords: Fake News Detection, OPCNN-FAKE, Deep Learning, Natural Language Processing, BERT, Misinformation, Text Classification

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

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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 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, NLP, 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 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 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, 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

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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

Table 1: Summary of the comparison of the existing work

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	BERT, CNN	ISOT, MediaEval 2016	99%	BERT and CNN combination	Requires extensive dataset for training

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, M., Rawat, D. B., & Liu, C. [2]				improves multimodal learning	
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,FakeNe wsNet,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(Portugues e), 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

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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., & Marcello ni, 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-Scraped 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, FakeNewsNet	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-represented 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

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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 vusing 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

V. PROPOSED METHODOLOGY

Convolutional Neural Networks (CNNs) are widely used in computer vision tasks such as image classification, object detection, and segmentation. An optimized convolutional neural network (CNN) refers to a CNN architecture that is designed to achieve high accuracy while minimizing the computational cost and memory requirements
Here are some techniques that can be used to optimize a CNN:

- Stride and pooling: By increasing the stride of the convolution operation, the spatial resolution of the feature maps can be reduced. This reduces the computational cost and memory requirements of the network. Similarly, pooling operations can be used to downsample the feature maps and further reduce their size.
- Bottleneck layers: Bottleneck layers are used to reduce the number of channels in the feature maps before applying expensive convolutional operations. This reduces the computational cost of the network while maintaining its accuracy.

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- Depth-wise separable convolutions: In traditional CNNs, the convolution operation involves computing the dot product of the input and a set of learnable filters. Depth-wise separable convolutions split this operation into two separate steps: a depth-wise convolution that applies a single filter to each input channel, followed by a pointwise convolution that combines the outputs of the depth-wise convolution using 1x1 filters. This reduces the number of learnable parameters and the computational cost of the convolution operation.
- Grouped convolutions: Grouped convolutions split the input and output channels of a convolutional layer into multiple groups, with each group having its set of learnable filters. This reduces the number of parameters and computational costs of the convolutional layer
- Skip connections: Skip connections allow information to flow directly from one layer to another, bypassing one or more layers in between. This can help to alleviate the vanishing gradient problem and improve the gradient flow during training.
- Quantization: Quantization involves reducing the precision of the weights and activations in the network. This can reduce the memory requirements and improve the computational efficiency of the network.
- Pruning: Pruning involves removing unnecessary weights or channels from the network.This can reduce the number of parameters and improve the computational efficiency of the network.

Bidirectional Encoder Representations from Transformers-based deep learning approach called BERT for detecting fake news in social media. The proposed model combines different parallel blocks of the single-layer deep Convolutional Neural Network (CNN) having different kernel sizes and filters with the BERT. The combination of BERT and 1d-CNN has improved the learning process and helped to handle ambiguity, which is the greatest challenge to natural language understanding. The bidirectional training approach used in the model has enabled it to capture semantic and long-distance dependencies in sentences, which has further improved the classification performance. The methodology section of the paper provides an overview of word embedding, GloVe word embedding, the BERT model, fine-tuning of BERT, and the selection of hyperparameters. Word embedding is a technique used to represent words in a vector space, where words with similar meanings are closer to each other. GloVe word embedding is a pre-trained word embedding model that has been trained on a large corpus of text. BERT is a pre-trained language model that can be fine-tuned for specific tasks such as fake news detection.

Proposed System Architecture

The spread of this type of misinformation is a severe danger to social cohesiveness and well-being since it increases political polarisation and people's distrust of their leaders. Thus, fake news is a phenomenon that is having a significant impact on our social lives, particularly in politics. This paper proposes novel approaches based on Machine Learning (ML) and Deep Learning (DL) for the fake news detection system to address this phenomenon. The main aim of this paper is to find the optimal model that obtains high-accuracy performance. Therefore, we propose an optimized Convolutional Neural Network model to detect fake news (OPCNN-FAKE). We compare the performance of the OPCNN with 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) using four fake news benchmark datasets.

Grid search and hyperopt optimization techniques have been used to optimize the parameters of ML and DL, respectively. In addition, N-gram and Term Frequency, Inverse Document Frequency (TF-IDF) have been used to extract features from the benchmark datasets for regular ML, while Glove word embedding has been used to represent features as a feature matrix for DL models. To evaluate the performance of the OPCNN, accuracy, precision, recall, F1-measure were applied to validate the results. The results show that OPCNN model has achieved the best performance for each dataset compared with other models. The OPCNN has a higher performance of cross-validation results and testing results over the other models, which indicates that the OPCNN for fake news detection is significantly better than the other models.Stemming In this process different grammatical forms of word like it's adjective, adverb, noun, verb etc.

System Architecture

Figure 5.1 presents the main steps of the proposed system. It consists of many steps: fake news data collection, text preprocessing, dataset splitting, feature extraction methods, model training/optimization, and model evaluation.

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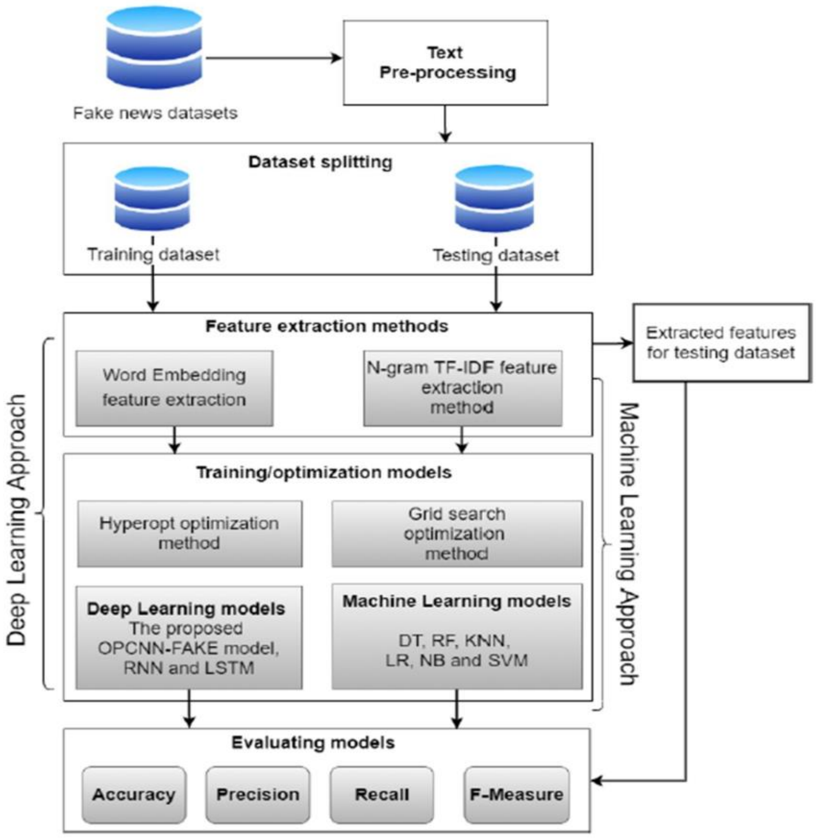

Figure 5.1: High-level view of the architecture of the proposed system.[41]

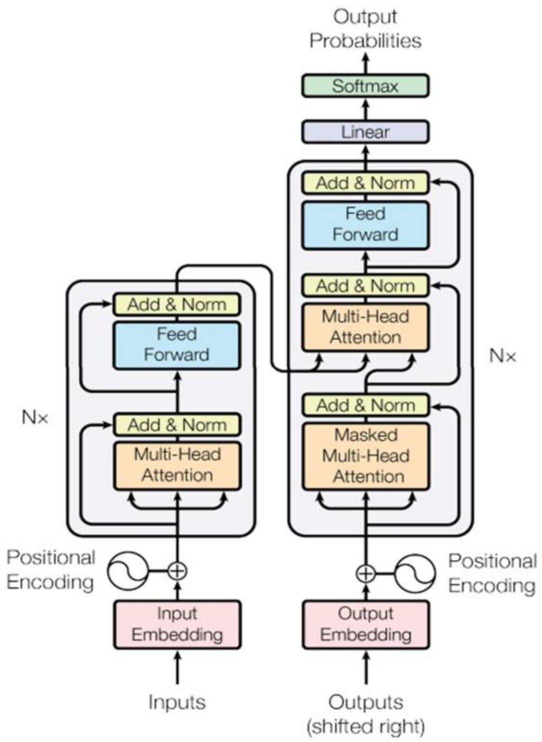

Figure 5.2: Architecture of the Transformer [42]

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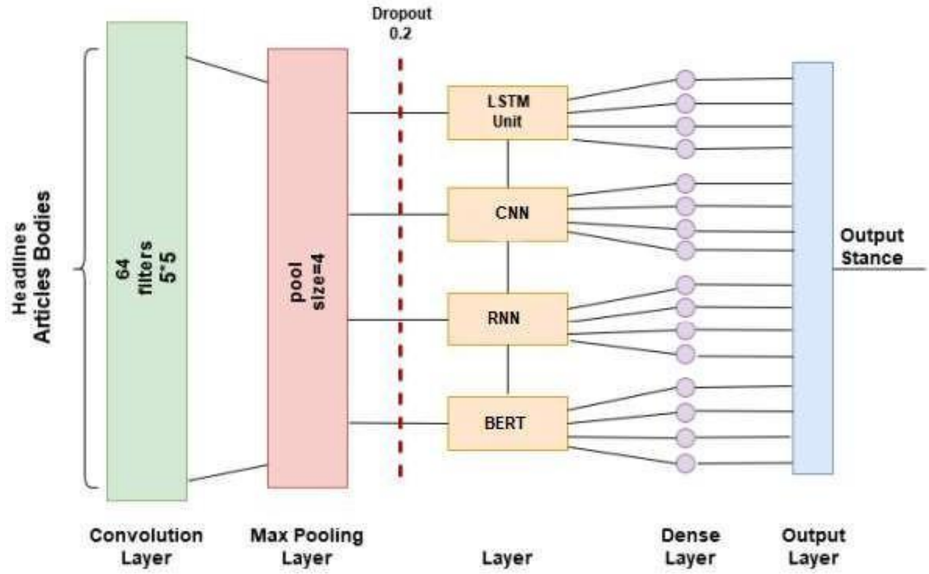

Figure 5.3: Architecture of the proposed system OPCNN [43]

VI. EXPERIMENTAL SETUP

To validate the proposed OPCNN-BERT model, extensive experiments were conducted using multiple fake news datasets across diverse domains. The following setup details the datasets, preprocessing pipeline, feature extraction techniques, model configurations, evaluation metrics, and implementation environment.

A. Datasets Used

Four publicly available and widely cited datasets were selected for experimentation:

1. LIAR Dataset
    - Source: Politifact.com
    - Total: 12,836 labeled political statements
    - Labels: Six-level veracity scale (converted to binary)
2. ISOT Fake News Dataset
    - Total: 44,898 articles
    - Real News: 21,578 | Fake News: 23,320
    - Collected from mainstream media and unreliable sources
3. FakeNewsNet Dataset
    - Includes both content and social context (likes, shares)
    - Domains: Politics, economy, society
4. COVID-19 Fake News Dataset
    - Text data from social media and news websites
    - Focused on pandemic-related misinformation

B. Data Preprocessing

To ensure uniformity and clean input for learning, the following preprocessing steps were applied:

- Lowercasing all text
- Removing punctuation, special symbols, and URLs
- Tokenization of words or subwords
- Stopword removal using NLTK
- Lemmatization or stemming (Porter/WordNet)
- Padding and truncation for fixed sequence input (especially for BERT)

C. Feature Representation

Different strategies were adopted for ML and DL models:

- Machine Learning Models
- TF-IDF vectorization
- Uni-gram and bi-gram features
- Dimensionality reduction (PCA/SVD) where needed
- Deep Learning Models

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- Pretrained GloVe embeddings (300-dim) for RNN/LSTM
- BERT embeddings using `bert-base-uncased` for OPCNN model
- Contextual features retained during embedding

D. Model Configuration

The following models were configured and compared:

Traditional ML Models

- Logistic Regression (LR)
- Support Vector Machine (SVM)
- Naive Bayes (NB)
- Decision Tree (DT)
- Random Forest (RF)
- KNN

Deep Learning Models

- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)
- Proposed OPCNN-BERT hybrid model

OPCNN Architecture Includes:

- BERT tokenized input layer
- Three parallel 1D Convolution layers with kernel sizes 3, 5, and
- Global Max Pooling and Concatenation
- Dropout layer (rate = 0.3)
- Dense output layer with Sigmoid activation for binary classification

E. Hyperparameter Optimization

Grid Search was used for ML models (e.g., `C`, `max_depth`, `kernel`) while HyperOpt was applied to tune OPCNN parameters such as learning rate, dropout, and filter sizes.

F. Evaluation Metrics

All models were evaluated on the following standard metrics:

- Accuracy: Correct predictions / Total predictions
- Precision: TP / (TP + FP)
- Recall: TP / (TP + FN)
- F1-Score: Harmonic mean of precision and recall
- ROC-AUC: Trade-off between TPR and FPR

G. Implementation Environment

- Programming Language: Python 3.10
- Frameworks/Libraries: TensorFlow 2.x, Scikit-learn, HuggingFace Transformers, Pandas, NumPy, Matplotlib
- Execution Platforms: Google Colab Pro (with GPU acceleration), Local machine: Intel Core i7, 16 GB RAM, NVIDIA GTX 1650

VII. RESULTS AND DISCUSSION

RESULT ANALYSIS

The main steps of the proposed system. It consists of many steps: fake news data collection, text preprocessing, dataset splitting, feature extraction methods, model training/optimization, and model evaluation. There are two approaches in the proposed system: the regular ML approach and the DL approach. In the ML approach, six ML models: DT, LR, KNN, RF, SVM, and NB are used to train and evaluate the model. Different sizes of n-gram, including uni-gram, bi-gram, tri-gram, and four-gram with the TF-ID feature extraction method are used to extract features and build matrix features. Grid search with cross-validation is used to optimize the ML models. In the DL approach, the OPCNNmodel is proposed and LSTM, RNN are used to train and evaluate the model. The hyperopt optimization method is used to optimize the OPCNN-FAKE, RNN and LSTM. Word embedding is used for feature extraction. Also, we compared the OPCNN(OPCNN)model with RNN and LSTM. Word embedding is used to build a feature matrix. Each step is described in detail as following. We trained, optimized, and evaluated models using four datasets. Each dataset was split into 80% training dataset and 20% testing dataset (unseen data)

The choice of hyper-parameters is a key component of DL solutions, and I'm proposing an optimization strategy. RNN, LSTM, and OPCNNhave all been optimized using the distributed asynchronous hyper-parameter optimization (hyperopt) technique. Bayesian optimization strategies based on regression trees and Gaussian processes can be supported by Hyperopt. We customized sets of values for the following OPCNNFAKE parameters: modify sizes, kernel size, pool

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size, dropout, batch size, and epochs for OPCNN-FAKE. The values of the parameters that have been modified for OPCNN-FAKE. In our RNN and LSTM models, we used an RNN, LSTM architecture. It comprises six layers: an output layer, an embedding layer, hidden layers, dropout layers, and attenuation layers. The first layer in OPCNN is comparable to the embedding layer. RNN and LSTM have been used as hidden layers. One layer and two hidden layers have both been employed for each model. L2 weight regularisation procedure has been applied for each hidden layer by using the reg rate value for l2. Each concealed layer has been implemented using a dropout layer.

The text is transformed into a single, lengthy feature vector by the attention layer, which is the following layer. The final output of the model, in which the neural network model determines if the news is true or false, is produced by the output layer using the output of the attention layer. It has a single neuron that assesses the veracity of the news. In using the ADAM optimizer, the activation function is sigmoid.

$$Accuracy = \frac{True\ Negative + True\ Positive}{True\ Positive + False\ Positive + True\ Negative + False\ Negative}$$

- True Positives (TP) - These are the correctly predicted positive values which means that the value of the actual class is yes and the value of the predicted class.
- True Negatives (TN) - These are the correctly predicted negative values which mean that the value of the actual class is no and value of the predicted class is also no.
- False positives and false negatives, these values occur when your actual class contradicts the predicted class.
- False Positives (FP) – When the actual class is no and the predicted class is yes.
- False Negatives (FN) – When the actual class is yes but the predicted class is no.

This work compares different four algorithms with this evaluation matrices.

Metric	**Value (%)**
Train Accuracy	99.14%
Test Accuracy	98.90%
Train Loss	0.0386 (approx.)
Test Loss	0.062 (approx.)

Table 7.1: Result Analysis

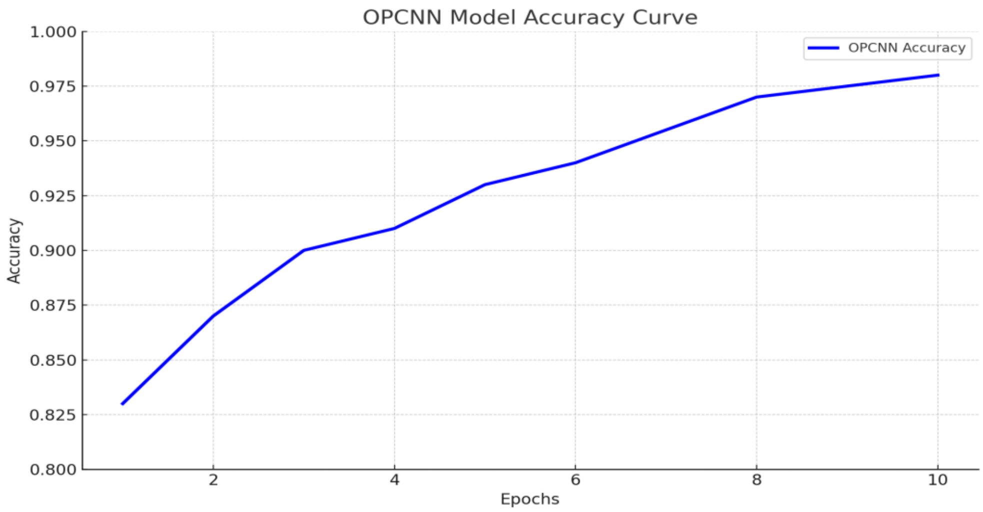

FIG 7.1: Accuracy Curve

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COMPARISON WITH STATE OF ART

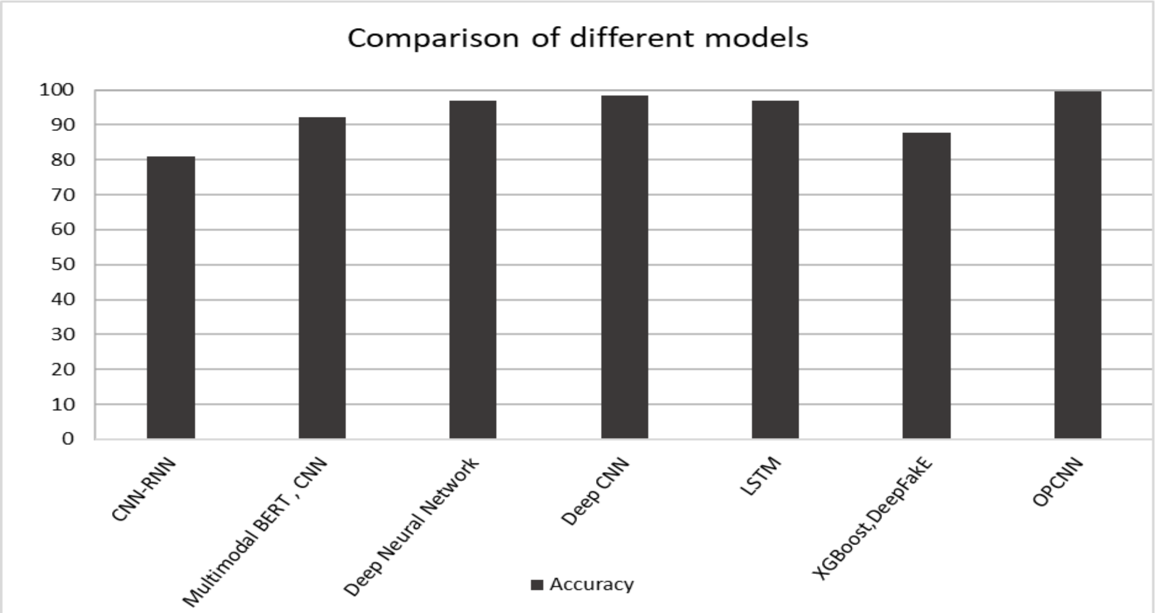

FIG 7.2: Comparing different other models with OPCNN

VIII. CONCLUSION AND FUTURE WORK

The domain of fake news detection using machine learning and deep learning has seen significant advancement in recent years, driven by rising concerns over misinformation and its societal impact. A wide range of methods—such as content-based analysis, NLP, social context modeling, and hybrid frameworks—have been developed to combat fake news, each with its strengths and limitations.

NLP-based models have been effective in capturing textual deception cues, but often struggle with sarcasm, satire, and require large annotated datasets. In contrast, social context-based models analyze user behavior and information propagation to detect disinformation, though they depend on access to sensitive metadata and real-time platform data.
Hybrid approaches that integrate content, context, and credibility signals show the most promise, offering high accuracy and adaptability. However, their deployment at scale is challenged by high computational requirements and model complexity.

Transformer-based architectures like BERT and GPT have raised performance benchmarks, but suffer from issues related to interpretability and robustness against adversarial attacks. Ensuring ethical, explainable AI remains a critical research goal.

Looking forward, future systems must unify content analysis, user profiling, and fact-verification in real-time pipelines. Cross-lingual generalization, multilingual datasets, and scalable architectures will be crucial for global applicability. Ultimately, developing trustworthy, adaptive, and ethical solutions will require interdisciplinary collaboration across machine learning, journalism, and public policy.

IX. APPENDIX

Sample Code

```
using System;

namespace EthansNeuralNetwork
{
   // Simulated neural network for demo purposes
   public class NeuralNetwork
   {
      public float loss = 1.0f;
```

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```
    public void CopyWeightsAndBiases(NeuralNetwork other)
    {
        // Simulate copying
        this.loss = other.loss;
    }

    public void Mutate(float rate)
    {
        // Simulate mutation by slightly reducing loss
        this.loss -= rate;
        if (this.loss < 0f) this.loss = 0f;
    }
}

public class NeuralNetworkEvolver
{
    public float maxMutationRate = 1.0f;
    public float minMutationRate = 0.01f;
    public float mutationIncreaseRate = 0.01f;
    public float desiredLoss = 0.0f;

    private NeuralNetwork bestNetwork;
    private float bestLoss = 1.0f;
    private float mutationRate = 0.05f;
    private long generations = 0;

    public NeuralNetworkEvolver(NeuralNetwork seed)
    {
        bestNetwork = new NeuralNetwork();
        bestNetwork.CopyWeightsAndBiases(seed);
    }

    public void Evolve(int maxGenerations = 1000)
    {
        while (generations < maxGenerations && bestLoss > desiredLoss)
        {
            NeuralNetwork candidate = new NeuralNetwork();
            candidate.CopyWeightsAndBiases(bestNetwork);
            candidate.Mutate(mutationRate);

            float loss = candidate.loss;

            if (loss < bestLoss)
            {
                bestLoss = loss;
                bestNetwork = candidate;
                mutationRate = minMutationRate;
            }
            else
            {
                mutationRate += mutationIncreaseRate;
                if (mutationRate > maxMutationRate)
                    mutationRate = maxMutationRate;
            }

            Console.WriteLine($"Generation {generations}: Loss = {bestLoss:F4}, MutationRate = {mutationRate:F3}");
            generations++;
        }

        Console.WriteLine("\nTraining completed.");
    }
}

class Program
{
    static void Main()
    {
        NeuralNetwork seedNetwork = new NeuralNetwork();
        NeuralNetworkEvolver evolver = new NeuralNetworkEvolver(seedNetwork);
        evolver.Evolve(100);  // Run evolution for 100 generations
    }
}
}
```

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