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An Advanced Intelligent Model for Fake News and Spam Call Detection †

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Abstract

The goal of this research is to develop an advanced intelligent model capable of identifying spam calls and fake news, while also enhancing the reliability and accuracy of spam detection. Available models face numerous challenges, including low accuracy, high error rates, slow processing speeds, and difficulties in handling noisy, unbalanced, and complex datasets. To overcome these disadvantages, the current work presents a new model, known as the Arctic Puffin-based Convolutional Detection Model (APbCDM). This model incorporates suitable preprocessing methods with the Arctic Puffin Optimization (APO) algorithm to extract meaningful features and suppress noise in the dataset. It then applies the filtered features through a convolutional network for appropriate classification. The results of the experiment indicate that the model proposed in this paper achieves an accuracy level of 99 percent. It also has precision, recall, and F1-score levels of 99 percent, along with a low error rate of just 1 percent, clearly indicating its superiority over traditional methods. The current work presents a robust, precise, and intelligent approach to detecting spam calls and fake news. Index Terms—Fake News, Convolutional Neural Network, Data Preprocessing, Feature Selection, Spam Call Detection.

Keywords: fake news detection; spam call detection; machine learning; deep learning

1. Introduction

Social media and digital platforms have become the primary source of news, particularly among young people, as they are more likely to accept new information without critical evaluation [1]. As a result, fake news proliferates, threatening democratic stability and eroding trust in institutions related to elections and social issues [2]. In addition, fake news garners more engagement compared to factual news on social media, resulting in a more significant concern [3]. There has been an increasing amount of data, making it even more relevant to utilize computational approaches to monitor fake news using artificial intelligence (AI) [4]. Detecting fake news necessitates the utilization of AI because AI can analyze language and context more thoroughly than any typical human [5]. With the emergence of AI and Natural Language Processing (NLP) technologies, new methods and new avenues for research have evolved [6]. The web is fundamentally complex, with large

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volumes of diverse content, making it necessary to use automated detection to ensure information is of adequate integrity and quality [7]. This research proposes a suite of Machine Learning (ML) and Deep Learning (DL) methods, inclusive of advancements in transformer-based models and FastText word embeddings on three public datasets for analysis [8], all with the ultimate goal of advancing the capacity to determine misinformation based on the data available [9].

Unwanted calls have become a significant problem worldwide [10]. According to reports, in 2020 alone, users received more than 31 billion spam calls, representing an increase from previous years [11]. Spam calls include telemarketing calls and scams that are completed either by live representatives or by robocalls [12]. In the US alone, there were 46 billion robocalls in 2020 [13]. To address this issue, various protocols, such as Call Detail Records (CDRs), are employed by telecommunications companies and governments to collect information about calls while respecting privacy [14]. Digital certificates for caller IDs, along with other technologies, have reduced unwanted calls; however, the technology continues to evolve, leaving users at risk [15]. In recent years, ML models and DL models have been used increasingly to combat fake news on online platforms and social media [16]. Common ML approaches, such as Logistic Regression (LR) and Support Vector Machines (SVMs), are entirely dependent on features derived from text statistics or metadata, which cannot characterize contextual relationships [17]. As such, a research agenda has begun to implement DL architectures and transformer models to facilitate a more semantic understanding of text [18]. However, there are still new issues and solutions to consider, such as the requirement for very large datasets, the ongoing shifting nature of fake news [19], and the limitations of models based on unimodal signals. Hence, adaptive and explainable models are being developed to improve generalization to context [20].

Spam and robocall detection technologies have evolved from simple rule-based filtering methods to ML and DL methods, such as Decision Trees (DTs), Gradient Boosting, and Neural Networks [21]. Recent methods include features derived from call logs and call metadata [22]. Studies have utilized graph neural networks (GNNs) to analyze call behavior across networks [23]. Despite this, challenges persist in the form of unbalanced datasets, privacy concerns, caller ID spoofing, and low latency, all of which affect model performance [24].

The key contributions of this work are described as follows:

- Initially, the fake news and spam call dataset was collected and prepared for training in the Python 3.1 environment.
- Hence, a novel Arctic Puffin-based Convolutional Detection Model (APbCDM) was developed to detect fake news and spam calls.
- Preprocessing was conducted to eliminate noise characteristics from the training database.
- Furthermore, meaningful features were examined and extracted using the Arctic Puffin Optimization (APO) algorithm.
- Subsequently, fake news and spam calls were detected by the APbCDM.
- Finally, the model's performance was validated and compared with existing approaches.

This research paper is organized into several sections. Section 2 reviews the relevant literature. The structure of the developed model is presented in Section 3. Section 4 presents the testing and results with applicable diagrams. Finally, the concluding remarks are given in Section 5.

2. Related Work

Some of the recent related literature reviewed for this study is summarized below.

Q. Zhang et al. [25] developed a recommended model that uses a Convolutional Neural Network (CNN) to detect fake news in short Chinese sentences. Instead of splitting

text into words, it divides each Chinese sentence into individual characters, which helps avoid common mistakes during word segmentation. Compared to existing methods, this technique offers high speed, higher training efficiency, and higher accuracy. However, one disadvantage is that CNNs cannot recognize long-term relationships in larger texts. In addition, more RAM is required.

E. Hashmi et al. [26] introduced a study that utilizes various ML and DL algorithms to detect fake news more effectively. It combines FastText word embeddings with models such as CNNs and Long Short-Term Memory (LSTM) networks, and also tests advanced models like BERT, XLNet, and RoBERTa. This technique achieves high accuracy, improved language understanding, and better generalization across datasets. However, advanced models require more training time, processing power, and larger datasets.

A. Gupta et al. [27] introduced the technology utilized in Call-E, which is based on NLP, allowing it to detect spam calls and fraudulent SMS messages in real time. The key benefits are that it provides immediate protection, keeps user data private, and does not gather or retain personal information. However, because it does not preserve user data, it is unable to learn from previous decisions and can mistakenly block essential communications.

N. Sharma et al. [28] introduced a study in which the Spam Call Prediction System utilizes ML, specifically Random Forest (RF) and Gradient Boosting, for the detection and blocking of spam calls and unwanted calls. Call data records and audio features are leveraged to classify calls as either spam or legitimate. The benefits include high accuracy, rapid prediction speed, and the ability to handle complex data. The disadvantages are that it takes longer to train and requires a large dataset to be effective.

L. Wu et al. [29] proposed a novel method called the MFIR algorithm to detect fake news, combining DL and text language analysis. It applies cross-modal fusion to integrate features without losing meaning, an inconsistency module to identify mismatched information, and an explanation layer to enhance interpretability. It excels in accuracy, interpretability, and multimodal data processing. Yet, it is not straightforward to train and requires high computational capability and large datasets.

3. Methodology

In this research, a new Arctic Puffin-based Convolutional Detection Model (APbCDM) was explicitly designed to detect fake news and spam calls. Initially, the fake news and spam call dataset was collected and prepared for training in the Python environment. Furthermore, preprocessing was conducted to eliminate noise characteristics from the training database. Moreover, the meaningful features were examined and extracted using the Arctic Puffin Optimization (APO) algorithm. Subsequently, fake news and spam calls were detected by the APbCDM. Finally, the model's performance was validated and compared with existing approaches. Figure 1 below illustrates the steps to build this model in a flowchart, for a more precise and accurate understanding.

3.1. Process of the Developed Model

APbCDM is an advanced DL framework for detecting fake news and spam calls, utilising CNNs and the Arctic Puffin APO algorithm [30]. The model contains several phases, starting with organizing and preprocessing the datasets to remove any irrelevant data. The APO algorithm assists with feature selection and tuning hyperparameters to enhance the CNN learning process by adjusting key parameters as needed, thereby improving performance and accelerating convergence. Through the use of multiple convolutional and pooling layers, APbCDM can leverage more comprehensive sets of textual and acoustic features, as well as fully connected layers, to identify complex relationships among these features. The classification layer accurately categorises inputs as either fake or real news,

and spam or regular calls, enabling reasonable predictions. With the inclusion of the APO algorithm, the model mitigates overfitting, enhances accuracy, and maintains computational efficiency, resulting in high detection rates and improved adaptability in applications.

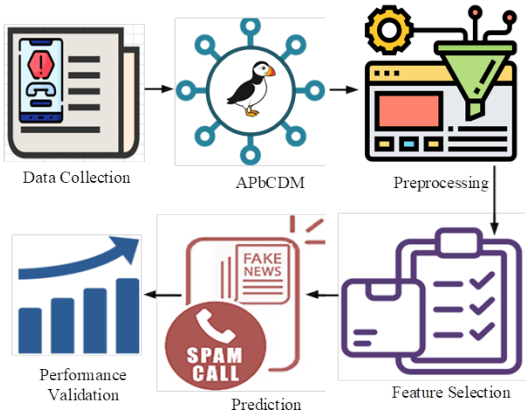


Figure 1. Proposed architecture of the APbCDM.

3.1.1. Data Collection

In the first stage, datasets containing fake news and spam call text logs are gathered from Kaggle sources. After the data are collected, the datasets are imported into the Python environment to run the training. Each text record is transformed into numerical form for training DL models. The data initialization process is mathematically represented in Equation (1).

$$d(f,s) = \{1,2,3,\ldots,k\} \tag{1}$$

Here, d indicates the collected data, f indicates the fake news data, s indicates the spam call data, and k denotes the total count of the data. After the data initialization process, preprocessing is started.

3.1.2. Preprocessing

Preprocessing is a critical step for cleaning and preparing raw text data for model training. The purpose of preprocessing is to refine the text by eliminating unwanted characters, numbers, stopwords, and duplicates. The data preprocessing process is mathematically represented in Equation (2).

$$P(d) = \left[(f-n),(s-n)\right] \tag{2}$$

Here, indicates the preprocessing variable, indicates the original data, and indicates the removed features. After the reprocessing, the feature selection process is executed.

3.1.3. Feature Extraction

Feature extraction through CNN layers utilizes Arctic Puffin Optimization (APO) to refine the best features. The APO algorithm is motivated by the intelligent foraging and migration behaviors of Arctic puffins. These behaviors work together to explore and exploit different parts of the search space to find high-quality solutions. Puffins explore by communicating with each other and adjusting their positions based on the best local and global solutions at the time. The feature extraction process is represented in Equation (3).

$$F_e = P_i^t + \alpha \cdot \left(P_{\text{best}}^t - P_i^t\right) + \beta \cdot \text{rand}() \cdot \left(G_{\text{best}}^t - P_i^t\right) \tag{3}$$

Here, F_e denotes feature extraction, P_i^t indicates the position of puffin i at iteration t, the best position of the puffin is denoted as P_{best}^t, and the global best position among all puffins is expressed as G_{best}^t. The terms α and β suggest the control coefficients for exploration and exploitation, and rand() indicates a random number in $[0, 1]$.

3.1.4. Prediction

When the most significant features have been identified through APO, they then flow into the fully connected layers of APbCDM for prediction. The model essentially performs a binary classification task to distinguish between fake news and real news, as well as spam calls and regular calls. The final output is derived from the model's last convolutional block, which uses a sigmoid activation to produce a probability score from 0 to 1, indicating the likelihood of the text instance belonging to the fake/spam class. The fake news prediction process is mathematically represented in Equation (4).

$$f_p = \begin{cases} \text{fake news}, & \text{if } F_e \geq 0.5 \\ \text{real news}, & \text{otherwise} \end{cases} \tag{4}$$

Here, f_p indicates the fake news detection process variable, 0.5 indicates the threshold value, and F_e denotes the predicted probability of fake news. The spam call prediction process is mathematically represented in Equation (5).

$$S_p = \begin{cases} \text{spam call}, & \text{if } F_e \geq 0.5 \\ \text{normal call}, & \text{otherwise} \end{cases} \tag{5}$$

Here, S_p denotes the spam-call detection variable, 0.5 indicates the threshold value obtained from APO, and F_e denotes the predicted probability of a spam call. Figure 2 illustrates the comprehensive framework of the proposed model development process, spanning from data collection to final predictions. It encompasses data preprocessing, feature selection, APbCDM architecture training, and performance evaluation.

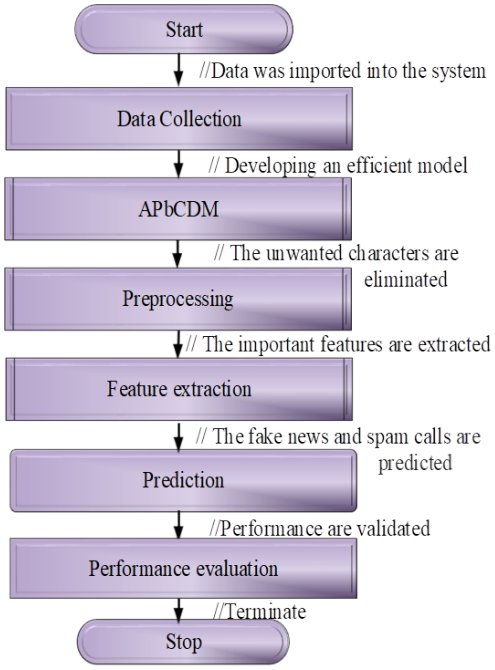


Figure 2. Flowchart of the proposed APbCDM framework.

4. Results and Discussion

The APbCDM was developed and tested in the Python environment to examine its capacity to detect fake news and spam phone calls. The model's performance was evaluated using performance metrics to verify its accuracy and reliability. The system was run on Windows 10 in the Python 3.8.10 environment, using the APO algorithm to optimize the CNN for superior learning and prediction. DL and optimization models were combined to achieve rapid training, enhance accuracy, and achieve efficient fake news detection. The system implementation configuration and parameters used in this study are presented in Table 1.

Table 1. Experimental setup specifications.

Parameter	Specification
Operating System	Windows 10
Programming Tool	Python
Python Version	3.8.10
Network Model Used	Convolutional Neural Network
Optimization Technique Applied	Arctic Puffin Optimization
Data Format	Textual Data
Name of the Dataset Used	Fake News and Spam Call Dataset

4.1. Comparative Analysis

To evaluate the ability of the proposed APbCDM to identify fake messages and spam calls, various performance metrics are used. The results indicated that the model was effective for differentiating between both authentic and fake data. The comparative evaluation also shows how the integration of the APO did improve the overall detection capabilities of the model when compared to the performance of the existing ML and DL models, including SVM, LR, RF, DT, Extreme Gradient Boosting (XGBoost), and LSTM [26].

4.1.1. Precision

The precision metric shows how many of the items predicted as positive (fake/spam) were actually correct. It shows how trustworthy the model is in making optimistic predictions. The calculation of precision is mathematically represented as Equation (6).

4.1.2. Recall

The recall metric indicates how well the model detects actual positives that were correctly detected. The recall calculation is given in Equation (7).

$$\text{Precision} = \frac{TP}{TP + FP} \times 100 \tag{6}$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100 \tag{7}$$

The developed APbCDM model outperformed other models in terms of precision and recall, achieving 99% precision and 99% recall, compared to 97% for both values in SVM and LSTM, and 94% for both values in LR and XGBoost. The RF achieved 93% precision and 92% recall, while the DT performed the worst with 85% precision and 85% recall. The fluctuations in values indicate that the proposed model yields fewer false positives and detects nearly all fake news and spam calls with high accuracy, ensuring reliable classification results. The correlation between precision and recall is presented in Figure 3.

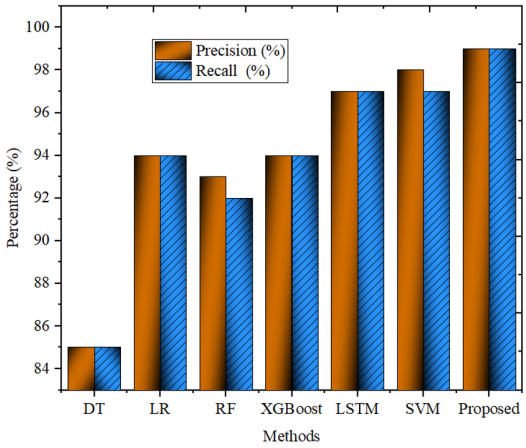


Figure 3. Correlation of precision and recall.

4.1.3. Accuracy

Accuracy shows the accurate predictions for both positive and negative classes. The calculation of accuracy is mathematically represented as Equation (8).

4.1.4. F1-Score

The F1-score is simply the harmonic mean of Precision and Recall, which provides a balanced metric in cases of unequal class distribution. The F1-score is presented in Equation (9).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{8}$$

$$\text{F1-score} = 2 \times \left(\frac{P \times R}{P + R} \right) \times 100 \tag{9}$$

Here, TP indicates the correct positive values, TN represents the true negative values, TN denotes the false positive, and FP indicates the false negative values from the dataset.

The results of the comparisons showed that in this study, the APbCDM achieved the highest overall performance compared to the other models from the experiments. The innovative approach achieved a 99% accuracy and F1 Score, both above those of the following closest models: SVM (97%), LSTM (97%), LR (94%), XGBoost (94%), RF (92%), and DT (85%). This clearly indicates that the APbCDM can identify fake messages and spam calls more consistently and accurately, achieving a high balance between recall and precision. The correlation of the accuracy and F1-score is presented in Figure 4.

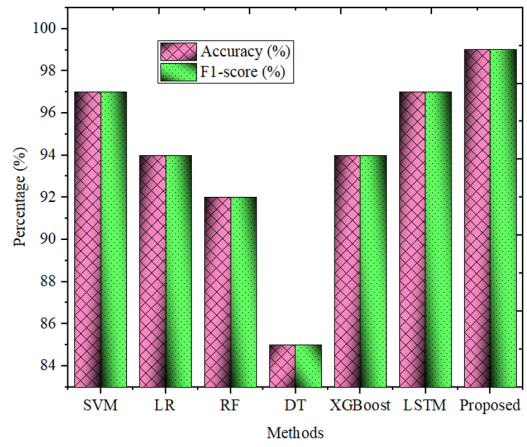


Figure 4. Correlation of accuracy and F1-score.

4.1.5. Error Rate

Error rate is the percentage of incorrect predictions compared to all predictions. The error rate is mathematically presented in Equation (10).

$$\text{Error Rate} = 100 - \text{Accuracy} \tag{10}$$

The error rate correlation is represented in Figure 5. The recommended model shows a very low error rate of 1%, which is significantly lower than SVM (3%), LSTM (3%), LR (6%), XGBoost (6%), RF (8%), and DT (15%). This very low error rate indicates the model's excellent prediction capabilities with very few misclassifications. The proposed APbCDM model outperforms all previous approaches in detecting fake news and spam calls, demonstrating its effectiveness and robustness. The entire comparison is presented in Table 2.

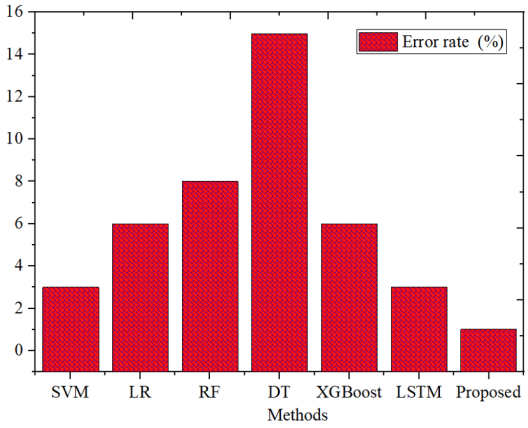


Figure 5. Correlation of error rate.

Table 2. Performance Comparison of Classification Models.

Model	Precision (%)	Recall (%)	Error Rate (%)	Accuracy (%)	F1-Score (%)
SVM	98	97	3	97	97
LR	94	94	6	94	94
RF	93	92	8	92	92
DT	85	85	15	85	85
XGBoost	94	94	6	94	94
LSTM	97	97	3	97	97
Proposed	99	99	1	99	99

4.1.6. Discussion

The APbCDM was proposed as a viable model for detecting fake news and spam calls. Its stability and efficiency were evaluated against those of traditional ML and DL models. The proposed model was found to demonstrate better predictive capability and stability. Table 3 summarises the proposed model's performance. The APbCDM achieved 99% accuracy, a remarkable result, indicating its strong ability to classify data accurately. With over 99% precision/recall rates, the model can detect fakes and spam with minimal false positives and false negatives. The model's F1-score is also equal to 99%, indicating not only its accuracy but also its consistency and balance across all evaluation measures. Furthermore, the model achieved an error rate of 1%, indicating a high level of accuracy and robustness. This also proves that the APbCDM performed exceptionally well compared to traditional detection techniques.

Table 3. Performance Achievements of the Proposed Model.

Metrics	Achievements
Accuracy	99%
Recall	99%
Precision	99%
Error Rate	1%
F1-score	99%

5. Conclusions

In summary, the developed APbCDM framework is a highly effective and intelligent method for identifying both fake news and spam calls. By integrating good data preprocessing techniques and the APO algorithm into the model, noise was filtered, and the most important and relevant features were extracted from the data, enhancing training and detection performance. Relative to the existing models, the APbCDM demonstrated an impressive accuracy of 99%, precision of 99%, recall of 99%, and an F1-score of 99%, while also attaining a lower error rate of 1%. This illustrates the strength and trustworthiness of the model in determining the class of fake or spam, while producing a limited misclassification rate. However, the study has limitations, specifically the quality and size of the training database, which also require significant computational resources to train the model. Future efforts may benefit from further improving the model by integrating deep transformer-based architectures to improve context understanding and gain scalability.

Author Contributions: Conceptualization, C.T. (Chaitanya Tumma) and S.A.; methodology, C.T. (Chaitanya Tumma) and N.S.; software, C.T. (Chaitanya Tumma) and S.A.; validation, S.A. and S.B.R.; formal analysis, S.A. and S.B.R.; investigation, C.T. (Chaitanya Tumma) and S.B.R.; resources, S.A. and C.T. (Chaitanya Tumma); data curation, N.S. and S.B.R.; writing—original draft preparation, C.T. (Charan Thumma), C.T. (Chaitanya Tumma) and S.B.R.; writing—review and editing, C.T. (Chaitanya Tumma) and S.B.R.; visualization, C.T. (Chaitanya Tumma) and N.S.; supervision, S.B.R.; project administration, C.T. (Charan Thumma), S.A., C.T. (Chaitanya Tumma) and S.B.R.; funding acquisition, C.T. (Chaitanya Tumma), N.S. and S.B.R. All authors have read and agreed to the published version of the manuscript.

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