Image Fake News Prediction Based on Random Forest and Gradient-boosting Methods

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Abstract The internet technology of today makes it challenging to spread false information, particularly through photos, including fake news. In this study, fake news is identified and predicted using photos that have been altered or misrepresented. Effective detection systems are crucial because of the proliferation of false information that images might spread due to the use of image modification tools and social media. This paper provides a thorough analysis of fake news based on images. Among the main research areas are machine learning for classification models and image data embedding (feature extraction). Our novel methodology forecasts fake news in the form of altered or misleading photographs by using Random Forest and gradient-boosting algorithms to detect visual alterations such as picture editing and image synthesis. This research leverages massive image datasets from news channels and social media to train and assess predictive algorithms. Our results demonstrate that our method has strong recall and precision in identifying image-based fake news. We also discuss practical applications and real-time detection, such building tools to combat misinformation on social media and in news organizations. At 0.968 with 0.997, Gradient Boosting performs better than Random Forest.

INTRODUCTION

Nowadays, there is a paradigm shift in the way that consumers consume news. In order to swiftly obtain more information, they primarily search social media platforms for news summaries [1]. This shift is the result of news being easily accessed and shared on social media sites like Facebook and Twitter. Malicious users of this platform take advantage of this unavoidable dependency to disseminate false photos. Digitally altered photographs that have undergone many changes are called fake images. A great example of a phony image is a morphed image, in which one person's face is substituted for another. These days, it is frequently employed to spread misinformation or a story under a political umbrella. False information on the coronavirus was surveyed by the Norwegian Media Authority in Norway [2]. The study's conclusions indicated that the most important factor in the dissemination of incorrect information was social media, particularly microblogging sites. Similarly, Facebook and Twitter are the two most popular sites for disseminating fake news, according to a poll done by Internet Society and CIGI-IPSOS [3]. The main content used in the dissemination of fake news is bogus photos and videos. More people are drawn to fake visuals than to words. Fake photos and films have occasionally had serious consequences. Global digital behemoths such as

Facebook, Google, and Adobe are investing in the creation of artificial intelligence (AI) apps in an effort to combat the proliferation of bogus photos and movies on the internet. Because fake news has a greater impact than text, it is increasingly using bogus images. Images alter how people remember and process information for psychological reasons [4]. Similar findings were reported in Adobe's 2015 State of Content survey results, which indicated that posts containing graphics received three times as much interaction as ones containing only text [5]. According to a survey by the activist organization Avaaz, Facebook's major source of health misinformation poses the greatest harm to public health [6]. As a result, developing methods to identify bogus photos on social media is vital. It will take time to investigate the spread of altered photos and lessen their negative effects on the public. In this research, we suggest a modal strategy that applies SqueezeNet for feature extraction and then applies the new and improved models to forecast fake photos. AdaBoost and Random Forest, two cutting-edge machine learning techniques, were used to complete multi-class categorization. This paper is organized as follows: Section 2 will deal with the categorization of related works. Part 3 provides an example of the suggested process. An explanation of the findings and a classification discussion are given in Section

4. Section 5 concludes with exploring the issue of prospects and conclusion.

RELATED WORK

Much effort has been put into image fake categorization. Previous work focused on extracting image features and was called image fake news categorization. Using Random Forest and AdaBoost Algorithms for the document images in our proposed paper. In this related work. Singh and Sharma [7] detected phony images on social media by using a customized CNN model with high-pass filters. A CNN model was presented by Johnston et al. [8] to identify and locate tampered regions in edited films. To recognize and label the tampered regions in videos, the model used CNN to estimate a quantization parameter, intra/inter mode, and deblock setting of pixels patched up in videos. To detect false images, Vishwakarma et al. [9] suggested web scraping and picture reverse search. The generic, compact, and strong CNNs were utilized to analyze the input picture attributes in a different work by Roy et al.[10] .

A multimodal Fake News Detection model was developed by Kai Nakamura et al. Six categories are used to group samples from Reddit and Fakeddit for analysis. When combining class labels from various models, the functions Maximum, Concatenate, Add, and Average are employed. The best results are obtained with BERT for text and ResNet50 for image classification with maximum fusion. BERT+ResNet50 achieved 89.29% 2-way, 89.05% 3-way, and 86% 6-way classification accuracy using Maximum as a fusion approach.[11]

The ensemble multimodal approach for Fake News detection developed by Priyanka Meel and Dinesh Kumar V uses a Hierarchal Attention Network (HAN), Image Captioning, and Error Level Analysis. Max-voting combines model results. HAN, ELA, and Noise Variant Inconsistency are used to analyze images with embedded text (caption and comments), and Max fusion is utilized to obtain the Max vote class label. Modern techniques and human judgment were outperformed by the combined model on the Fake News Samples dataset. Accuracy for the ensemble model of the Fake News Sample was 94.7% .[12]

THE PROPOSED METHODOLOGY:

Using modal prediction, the research provides an efficient fake image prediction solution. The proposed model passes news and commercial detection picture modalities to feature extraction channels. The preferred model's architecture is shown in Fig. 2. It has five parts:
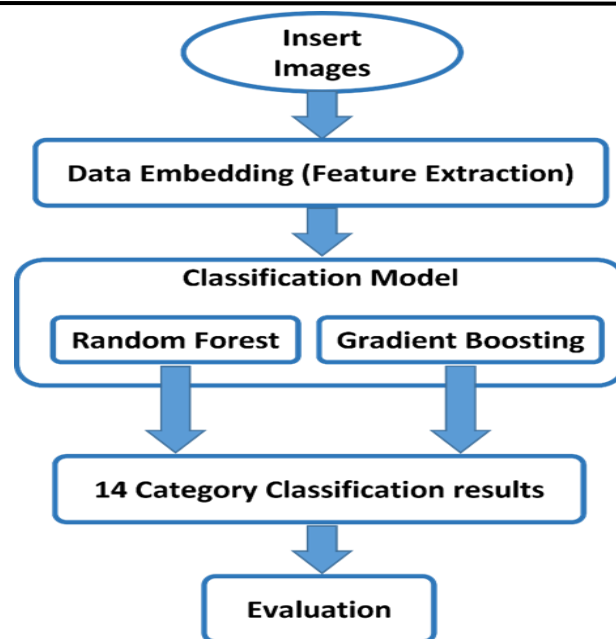

Fig. 1 An architecture of multiclass Fake News Prediction model.

It effectively conveys that the following subsections will delve into more detailed discussions of each phase.

1- Document Image Dataset: In the context of image fake news prediction. This paper depends on the data set news and commercial detection[13]. But we rely on only images for the prediction of fake images.

2- Feature Extraction: Fake news, especially picture manipulation, is a major issue in the digital age. Detecting and predicting image authenticity requires robust feature extraction methods. Efficient data embedding and feature extraction for image-based false news prediction is investigated using SqueezeNet, a lightweight deep neural network architecture. SqueezeNet operates in resource-constrained and real-time contexts because of its small design. We use SqueezeNet to extract features for image-based false news prediction in this study. The study focuses on data preprocessing, SqueezeNet feature extraction, and predictive modeling [14]. Many photographs from social media and news websites are first preprocessed. During preprocessing, scaling, normalization, and data augmentation improve model generalization. SqueezeNet obtains visual discriminative properties from preprocessed images. SqueezeNet's depth-wise separable convolutions and efficient design extract crucial image features while conserving processing resources. The model recognizes visual changes with the help of global and local elements.

3- Classification Model: In this section, a discriminative model is developed using the retrieved features from SqueezeNet to accurately differentiate between authentic and counterfeit images. To develop dependable classifiers, we explore a range of machine-learning methodologies, such as Random Forest and gradient-boosting Methods. Our goal is to utilize SqueezeNet's comprehensive feature representation to consistently and precisely predict fake news. Outlines the algorithm utilized to generate a model for document classification. Therefore, we collected 14 conclusions related to Category Classification. This section

demonstrates the utilization of two algorithms for the created model.

A. Random Forest:

This strategy enhances accuracy and reliability through the use of multiple decision tree models. The methodology includes variance reduction to mitigate overfitting and improve the accuracy of community-based decision trees. The robust ensemble learning technique, Random Forest, combines multiple decision trees to produce a single output. Its scalability and the capability to construct an uncorrelated forest of decision trees through bagging and feature randomness make it valuable for big data applications. Combining Random Forest with other algorithms further enhances document categorization [15].

B. Gradient Boosting:

Machine learning techniques like ensemble learning combine weaker models to create a more potent predictive model. This process involves training base learners, calculating residuals, and combining predictions. A learning rate parameter regulates the contribution of each model to avoid overfitting. Methods such as subsampling and depth control are employed [16].

4-   Evaluation: The evaluation of a classifier will be done using precision, recall, f-measure, and accuracy, sensitivity, and specificity are calculated as shown in (Eq. 1, Eq.2, Eq 3, Eq 4, Eq 5, Eq .6)[17-18].

$$Precision\ =\ TP/(TP + FP)(1)$$

The actual positive rate (T.P.) and false positive rate significantly impact positive instance recall or sensitivity.

$$Recall\ = \frac{TP}{TP + FN} \quad (2)$$

The following equation calculates accuracy, percentage of accurate predictions, and false-negative rate (F.N.).

$$Accuracy\ =\ (TP + FP)/(TP + TN + FP + FN)(3)$$

The term "T.N." means true negative, whereas "sensitivity" means the number of positive records that give the proper result.

$$Sensitivity\ =\ TP/TP + FN \quad (4)$$

Particularity is accurately arranging positive records from every positive paper.

$$Specificity\ =\ TN/TN + FP \quad (5)$$

The F-measure runs many data recovery accuracy norms and examines measurements.

$$F1\ Score\ =\ 2 * (Recall * Precision)\ /\ (Recall + Precision) \quad (6)$$

Correct classification employs True Positives (T.P.) and False Positives (F.P.), while incorrect classification uses False Negatives (F.N.). A test's document classification accuracy is determined by its sensitivity and specificity. The ROC curve illustrates the trade-off between true and false positives. When the emphasis is skewed, and false positives are ignored, the results are likely to primarily reflect the accuracy of genuine positives. Conversely, if true positives are neglected, and false positives are emphasized, the scores will reflect recall. The Area Under the Curve (AUC) measures classifier efficiency[19].

Results and discussion for classification:

The classification results using random forest and gradient-boosting methods on the dataset were used. The accuracy, precision, recall, and F1 score metrics are provided. The result is shown in Table 1

Table 1 The performance of various fake news classification algorithms

Model	AUC	CA	F1	PRECISION	RECALL
Random Forest	0.968	0.828	0.821	0.820	0.828
Gradient Boosting	0.997	0.922	0.921	0.923	0.922

Table 2 is a confusion matrix of a classification model's predictions for Gradient Boosting. The observer can determine how often the model is right (values along the diagonal) and how often it is incorrect (values off the diagonal) by comparing the actual class labels with those predicted by the model using the matrix. The labels in your matrix contain a variety of news channels and categories, with names like "fox_business," "fox_news," "msnbc," "the_weather_channel," "cbsn," "cnn," "espn," and "commercials" for each of these channels. The percentages display the kinds and rates of errors (off the diagonal) as well as the percentage of accurate predictions (on the diagonal, where predicted class = actual class). The colors most likely depict the magnitude of the values, with larger percentages matching to certain color intensities. In particular, if specific classes are frequently mistakenly assigned to one another, this matrix can be particularly helpful in determining where a model performs well and where it can be confused.

Table 2. Confusion matrix of a classification model's predictions for gradient boosting

While using Random Forest, the result in Table 3 is a confusion matrix of a classification model's predictions for Random Forest. The table provided a confusion matrix for a multi-class classification problem, specifically for classifying various categories across different fake news. Each row represents the true class, and each column represents the predicted class. The percentages within the matrix indicate the proportion of instances falling into each combination of true and predicted classes. How to interpret the confusion matrix: Rows: These represent the actual classes.

Columns: These represent the predicted classes. For example, let's take the first row: Cbsn (true class): 88.0% of instances with the true class "Cbsn" were correctly predicted as "Cbsn." 3.9% of instances with the true class "Cbsn" were predicted as "Commercial/cbsn." 1.6% of instances with the true class "Cbsn" were predicted as "Commercial/fox_news". and so on. Diagonal Elements (True Positives): The percentages on the diagonal represent instances where the true class and predicted class match. Higher percentages indicate accurate predictions. Off-Diagonal Elements (Misclassifications): Off-diagonal percentages represent instances where the model made a misclassification. The magnitude of these percentages indicates the extent of misclassifications. Column Sum: The sum of percentages in each column represents the predicted class distribution for each true class. Row Sum: The sum of percentages represents the distribution of true classes for each predicted class. This confusion matrix provides a detailed breakdown of the model's performance for each class. It can help identify which classes are well-predicted and where the model may have challenges.

Table 3. Confusion matrix of a classification model's predictions for random forest

The prediction model's ROC curve is shown in Figure 3 following the application of Random Forest and Gradient Boosting to multiple categorization criteria. Comparisons of ROC curves among various classifiers are commonplace, extending to Random Forest and Gradient Boosting.

Although the gradient-boosting model has a slight edge at some thresholds, both models essentially overlap and appear to function equally on the map you provide. High performance is indicated by both curves being in the upper-left corner of the figure. The classifier is flawless if the curves reach the upper left corner (0,1); if they follow the 45-degree line, the results are random.

For the majority of threshold values, both models show high TPRs and low FPRs, suggesting they are operating effectively. Understanding the work situation and doing a thorough examination of multiple performance metrics are necessary for selecting the best model. If the false positive cost of the application is large, you would prefer a model with a lower false positive rate. positive if the cost of false positives for the application is substantial.

Fig 3 Receiver Operating Characteristic (ROC) curve after using Random Forest and Gradient Boosting.

The following can be used to explain or understand the outcomes for the Random Forest and Gradient Boosting models:

Area Under the Curve, or AUC:

Random Forest: AUC of 0.968 shows that this model is quite good at differentiating between positive and negative examples.

Gradient Boosting: Even greater discrimination is suggested by an AUC of 0.997 or higher.

Classification Accuracy (CA): Random Forest: With an accuracy of 82.8%, the model was able to classify roughly 82.8% of examples correctly.

Gradient Boosting: Better overall performance in terms of accurate classifications, with a higher accuracy rate of 92.2%.

F1 Score: Random Forest: A harmonic mean of memory and precision of 0.821 indicates a balance between recall and precision.

Gradient Boosting: An improved balance between recall and precision is shown by a higher F1 score of 0.921.

Random Forest precision: 0.820 indicates that around 82.0% of the positive instances that were predicted were in fact true positives.

Gradient Boosting: A reduced percentage of false positives is shown by a greater precision of 0.923.

About 82.8% of real positive events were successfully identified, according to the Random Forest recall of 0.828.

Similar recall of 0.922 for gradient boosting indicates a high percentage of true positive identifications.

In conclusion, Gradient Boosting routinely beats Random Forest on all criteria, proving to be superior in terms of accuracy, discrimination, and striking a balance between precision and recall. Based on these findings, it appears that

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Gradient Boosting is a better model for the particular classification job.is a more effective model for the given classification task.

Fake news are accompanied by a lack of huge amounts of labelled data, due to the expensive nature of such endeavours. The proposed new techniques that can harness other resources to allow for a more robust implementation in a model workflow are essential. As future work attempts to bridge the gap between the Fake news image and text and technical world of machine learning by presenting a framework for training transformer-based models on challenging fake news datasets.

Table 4: related works reference the proposed approach.

No Reference	Feature selection method	Classifier Method	Highest performance in accuracy
[7] (2021)	-	A convolutional neural network detects social media photo fraud.	An accuracy of 92.3% i
[8] (2019)	-	H.264/AVC pixel patch quantization settings, deblock settings, and intra/inter mode are predicted using convolutional neural networks.	QP= (8) class and 71.18 Accuracy Inter/Intra= (2) class, and 69.23 accuracy Deblock = (2) class, and 66.53 accuracy
[9] (2019)	Text extraction from the image	An event is deemed real or fake based on its reality parameter (Rp), which is calculated based on a threshold.	85% accuracy
[10](2020)	Image features are collected using a visual geometry group (VGG) net.	CNN and LSTM are offered for assessing news reliability.	91.07%
[11](2019)	VGG16	created a multimodal false news detecting model: ResNet50 for image and BERT for text classification	With 89.29% 2-way, 89.05% 3-way, and 86% 6-way classification accuracy, BERT+ResNet50
[12](2021)	visual picture elements employing labeling and forensics.	HAN deep model for text, picture caption, headline matching, NVI, and ELA. These methods were tested individually and then together using max voting Ensemble on three datasets.	95.90%
The proposed mothed (2023)	feature extraction or data embedding using SqueezeNet	Gradient Boosting and Random Forest	**Random Forest** *is achieving accuracy (0. 0.968) while Gradient Boosting* is achieving accuracy (**0.997**)

CONCLUSION AND FUTURE WORK

Performance measurements and a confusion matrix from this research study show how well Gradient Boosting categorizes news photos. Gradient Boosting generally outperforms Random Forest in terms of AUC, F1 Score, Precision, Recall, and Classification Accuracy. The model's predictions for each class include areas of strength and room for improvement, as demonstrated by a thorough review of the confusion matrix. Gradient Boosting's accuracy and precision outperform those of other methods in a number of classes.

There may be challenges in differentiating between groups as indicated by greater rates of misclassification for certain classifications. In later work, use feature engineering to discover new or enhanced features and adjust hyperparameters to maximize the performance of the Gradient Boosting model.

Unequal Classification: Use an oversample, an undersample, or modify your sampling techniques to address the class imbalance. Interpretability techniques assist you in recognizing important components and comprehending the model's decision-making process. To improve categorization, combine models or apply ensemble approaches. Further investigation and improvement of these components may improve the performance and dependability of the model. Model evaluation and monitoring are necessary to adjust to data patterns..

Using Swin Transformer models [20] now become the ever-wanted architecture in many Fake news tasks, including classification [21], detection [22], and segmentation [23]. The main reason behind their success is the ability to incorporate global context information into the learning process [24]. By implementing Multi head-attention, recent developments in the Swin Transformer synthesis enable proposed structure to consider wide-values dependencies [25]. Hence it is

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convincing to propose such models with transformer based for the classification of histopathology fake news [26]. We will use as future work different hierarchical Meta-heuristic optimization algorithms as an encoder to extract global context features [26-30]. The multi-scale feature extraction based on hybrid transforms [31-35] in a Swin transformer enables the model to attend to different areas in the Fake news at different angels.[40-36]

Fake news detection is highly being studied through different online and different networking platforms, causing huge disruptions and effecting logical-decision perceptions [40-42]. Although the wide-spread importance of detecting fake news in several applications like newspapers, relatively few research efforts have been made to improve techniques like AI and ML oriented logical-detection models adapted to minimize resultant disruptions .[45-43]

Implementing hybridity of AI and ML case studies based on data collected from Iraq, Egypt, and Jordan, in future it is expected to improve developed a detection model aimed at using the previous mentioned techniques and metaheuristic optimization algorithms to model the situation [46-48]. It is hoped that the proposed model will be based on multiple data sources in order to study with evidence ts effectiveness in managerial decision-making .[51-49]

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