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A Predictive Intelligence Model for Fake News Detection on Online Media

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Abstract: *The spread of fake news in the present day has been a common occurrence especially in online social networks. Unverified news on social media have huge negative impact on public trust, political processes, and societal wellbeing. This research entails developing a predictive intelligence model for detecting fake news by using machine learning techniques. The study seeks to train it using articles from reliable news sources through web mining methods and then analyze news articles via NLP and ML algorithms to categorize it as either true or fake. The research methodology entailed detailed data preprocessing, text normalization, stemming, lemmatization, and sentiment analysis, to obtain linguistic and emotional markers mostly linked with fake news. The study uses a labeled dataset obtained from Kaggle repository which is used for training and evaluation. The research employs Bidirectional Encoder Representations from Transformers particularly for binary classification of Fake and Real News articles. Data Preprocessing steps like text normalization, stemming, lemmatization and sentiment analysis to extract linguistic and emotional markers are undertaken. Model performance is rigorously evaluated through precision, recall, and F1-score metrics, with particular attention to minimizing false positives/negatives in classification.*

Key Words: *Fake News; Predictive Intelligence; Machine Learning; NLP; Web Mining; Text Preprocessing; Sentiment Analysis; BERT; Supervised Learning; Classification Metrics.*

I.INTRODUCTION

The modern digital age generates substantial misinformation and news which develops into a global issue that damages both political choices and economic systems and social bonds. The fast distribution of information and news becomes achievable because people depend more on digital communication since social media continues to expand (Capuano et al., 2023). This research seeks to develop a machine learning approach that detect fake news and misinformation. Digital connectivity benefits established conditions where misinformation spreads freely through digital networks to give wrong and incorrect perception or picture. Public perception manipulation occurs when misinformation enters the system because this leads to social disruption that weakens trust between institutions and media platforms (Zhang et al., 2020). Political deception stands alongside healthcare misinformation and financial deceit and theoretical conspiracies as the primary forms of misinformation that affect different parts of society in various ways.

According to research by Grandon et al. (2021), artificial intelligence creates new opportunities for revolutionizing old keyword filtering methods. The detection abilities of context and intent are utilized by modern AI-based procedures. The accuracy of decision-making has increased substantially while the speed of decision processes has speeded up for both sentiment analysis and content moderation through current models. Rao et al. A new AI-based framework for context-aware analysis with machine learning algorithms is reviewed by Rao et al. (2020). According to Rao et al. Language features combined with metadata alongside user engagement actions deliver the most impact on how well software assigns categories (2020). The predictive intelligence model development objective harmonizes with the system because it uses multiple variables for input and adaptive learning functions. The application of AI for detecting patterns in fake news while making predictions simultaneously results in improved models with both precision and accuracy.

A new study by Ceylan, Wood and Madrid (2023) points out that fake news becomes popular on social media due to strong emotions. Results suggest that people are more likely to share false news because it has a bigger emotional effect than news with facts. Because of this, stories that aren't accurate get more views which means more people are likely to see them.

The issue turns up locally too. Faustine Ngila (2020) reported that Kenya has suffered an increase in fake news and bullying found on the internet, mainly during periods affected by politics. There has been an increase in Kenya of social media users having to deal with made-up stories on political, health and security subjects. As a result, individuals are deceived and society's unity is threatened as well as personal safety.

According to Tajrian et al. The authors of Tajrian et al. (2023) review different analysis methods for fake news and analyze their respective advantages and limitations. He above research shows that combining machine learning algorithms with feature extraction concepts in hybrid models offers more accurate outcomes and generalization performance than when using standalone models. Additionally, reviewing continuous model validation using different datasets is emphasized to ensure the effectiveness of the model across platforms and topics. This is in line with the focus of the current study which is to validate the accuracy, precision and reliability of the predictive model developed in order to maintain the effectiveness of the developed system in its real-world applications.

Problem Statement

False information propagation and its detection and mitigation have emerged as an key field of academic research in data science, natural language processing (NLP), and computational social science. The urgency of this challenge is emphasized by recent studies. As an example, Ceylan et al. (2023) indicate that fake news is shared about six times more than factual ones, which shows the disproportional role of misinformation in the online environment. Such dissemination is mainly through social media platforms, news websites, and instant messaging applications, especially. According to an article by Business Daily by Ngila (2020) reported that almost 86% of Kenyans have experienced and unintentionally shared false or inaccurate information on social media. To add to this, a survey by social media Lab Africa and the United States International University (USIU) indicated that 83.2% of the surveyed indicated that they had encountered biased or intentionally misleading information. These results indicate the ubiquitous character of misinformation and the need to create powerful predictive intelligence frameworks that would identify fake news with precision and effectiveness.

Objective of the study

To develop the intelligent model for detection of fake news

II.MATERIALS AND METHODS

In regard to data collection and sampling, the "Fake-Real News" dataset from Kaggle was used. This is one of the most popular datasets in the field of misinformation detection. It is important for developing and testing machine learning models that determine the difference between authentic and fake news stories. This dataset is particularly useful in natural language processing applications where one is trying to detect deceptive content.

The dataset contains one file with Fake news reports and the other with the Real news. It's a structured table format. The headline, full article text and the news category of each entry has been detailed in several attributes. The headline is more important because it usually works to attract the immediate attention of the reader, even using sensational language. The body of the publication/post is the full article and is the main source for linguistic structures such as tone, context, and narrative consistency, that all may be useful for evaluating the credibility of the content. Furthermore, having news categorized by subject, for example, political news or global affairs provides more context and can impact the way in which news authenticity is viewed.

The sizes of the article titles from the dataset is are varying with some articles having very many number of words. Padding was performed on all titles to limit them to 15 words in the tokenization stage. A histogram was plotted to review typical word length. As seen below, majority of the news articles hjave about 15 words.

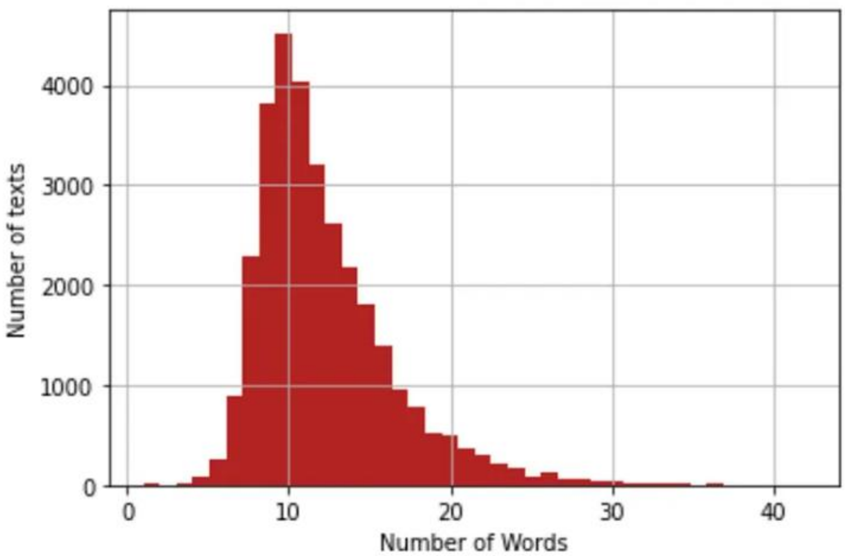

Figure 1. A histogram showing average word length per news articles titles.

Hugging Face transformers library and PyCaret were installed and the working directory was set to offer a model development environment. Pandas Data Frames were loaded with the imports of the true and fake news datasets in the form of CSV files. A column named Target was made to place each record with its class label (True or Fake), and the two datasets were combined into one, randomly mixed dataset. The nominal values in the Target column were coded in one-hot encoding (Fake = 1; True = 0). A pie chart was used to evaluate the distribution of the classes visually to have an equal representation of the two labels.

The combined data was divided into training, validation and test data in the ratio of 70:15:15 to enable model training, hyperparameter optimization and testing. The initial BERT weights were not updated in the course of fine-tuning, and only the additional layers were trained. The BERT network was followed by two thick layers with softmax activation. AdamW optimizer and a suitable loss function were established. Parameters of training, such as a batch size that fits the GPU and two epochs, were defined. PyTorch had functions to train and evaluate. The model was optimized using the training data and tested using the test set. The performance measures such as a classification report were produced to determine how the model distinguishes between fake and true news.

III.RESULT

The predictive intelligence model was tested with the help of standard evaluators of classification such as accuracy, precision, recall, and F1-score. These measures provide a deep insight into how the model can be used to differentiate between fake and real news. The classification model obtained after the BERT model was fine-tuned on a labeled Kaggle dataset attained an accuracy of 88 percent on the test set. This implies that there was almost 9 out of every 10 articles assigned correctly and therefore the level of model reliability was high. Below chart shows the performance of the model based on various parameters.

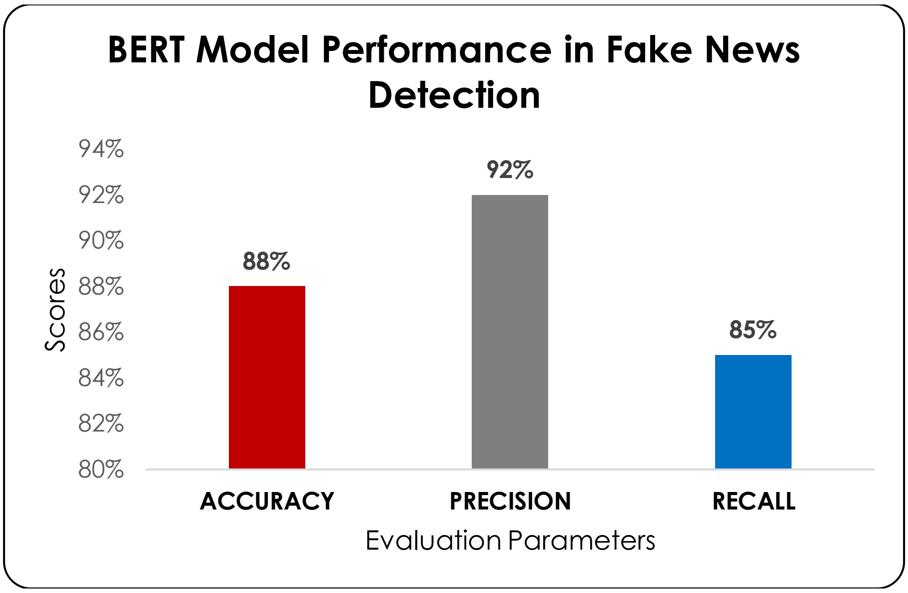

Figure 2. A comparison of various performance metrics on the model.

Key Findings

Accuracy of fake news: 92%

This means that when the model says that an article is fake, then it is right 92 percent of the time. It is an excellent indicator of how reliable the model is in minimizing false positives which is important in preventing the miscommunication of news that are actually true as false.

Fake news recall: 85%

This depicts the model performance in terms of correctly predicting 85 percent of actual fake news in the dataset. Although 100 percent is the best result, this number proves that the model is capable of identifying most cases of misinformation without a high percentage of false negatives.

The balanced metric between precision and recall, the F1-score, was high in the fake news class too, which indicates a good trade-off between sensitivity and specificity. To confirm the model generalization further, four news headlines were selected manually to run predictions on (there were two fake headlines selected and two real ones). The model recognized the four examples as correct and were in accordance with their real labels. Such a small but significant experiment on blind samples supports the effectiveness and feasibility of the designed system in the real-life settings.

These findings confirm the success of the method of fake news detection based on the BERT, a transformer-based NLP model. It is better at processing the context (in both directions) and semantics and sentiment that are frequently modified in the disinformation campaigns. The BERT model was much better than the traditional machine learning classifiers applied previously in the project (e.g., Naive Bayes, SVM) in all the evaluation metrics.

IV.DISCUSSION

The analysis of the linguistic and emotional features of the fake news showed that there are some patterns that were consistent throughout the data. In fake news articles, the choice of words is often charged, headlines are sensational, and there is an ambiguous source. The pre-processing and exploratory data analysis revealed that the words associated with conspiracy, nationalism, and fear were overrepresented in fake articles relative to real news.

The sentiment analysis proved that fake news tends to have excessive polarities either being too positive or being too negative which in turn tries to bring certain emotions out in the reader. Also, there were also language anomalies like excessive use of all-caps, exclamation points and clickbait-type titles that were also some of the most notable aspects of fake content. These findings are consistent with the available body of literature and validate the applicability of content-related features in identifying misinformation

V.CONCLUSION

A model that was created as a part of the research based on BERT showed strong results with an accuracy of 88 percent of correctly classifying news articles. More to the point, the precision of fake news identification stood at 92%, which means that the overwhelming majority of the items lurking as fake were the actual misinformation. Also, the model had a recall rate of 85%, which demonstrates that it is efficient in recognizing most fake news items without letting important cases pass unnoticed.

These findings not only confirm the validity of the use of transformer-based models in this task and their reliability and practicality but also prove the necessity of semantic and sentiment-sensitive processing to differentiate between real and fabricated stories. The model was able to generalize to data outside the training data, since it was able to classify the unseen test headlines, fake and real, with high accuracies.

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