Handling Imbalance Noisy Dataset By A Hybrid SMOTE-LOF-Transforms Model

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ABSTRACT
In In this study, we aim to evaluate the effectiveness of various machine learning models for fake news detection on PolitiFact and GossipCop datasets obtained from FakeNewsNet, focusing on identifying the most accurate and reliable model. We focused on using state-of-the-art methods combining deep learning transformers and SMOTE resampling techniques for class imbalance, LOF as outlying point detection. The proposed method in this paper, which combines the transformer attention mechanism with SMOTE and LOF resampling techniques, achieved the highest performance metrics on both datasets. The novelty of this model lies in its ability to train on a noisy imbalanced dataset in a short period of time while achieving high accuracy. It recorded an accuracy of 91.5% in PolitiFact and 87.2% in GossipCop, outperforming other models in accuracy, recall and F1 scores. Compared to models such as BERT, BERT + LSTM, and SAFE (multi-faceted), the attention mechanism stands out due to its ability to dynamically focus on relevant items. Overall, this work demonstrates the necessity of retraining models to accommodate the distinctive features of different datasets. It also demonstrates the effectiveness of attention mechanisms in understanding complex narratives and highlights the benefits of a multi-faceted perspective. This indicates that for realistic applications, choosing or designing models with high performance on multiple datasets is necessary, which may pave the way for future work on improving fake news detection using advanced NLP techniques and multimodal approaches.

Keywords: Deep Learning Transformers‹Fake News Detection, Local Outlier Factor (LOF). Synthetic Minority Over-Sampling Technique (SMOTE).

1. INTRODUCTION

In today's digital age, one of the major concerns of today's information society is the exponential growth of fake news on social media platforms. Not only does it distort public opinion, it erodes trust in legitimate news organizations, which represents a major threat to democratic health and public welfare[1]; Hence, it is now of utmost importance and an emerging aspect scientifically to identify and mitigate fake news sharing. The traditional way to detect fake news[2] It is divided into two families of methods: approaches based on content and strategies based on behavior. While the content-based approaches [3, 4] They are useful in some applications, but they are heavy in terms of big data processing and difficult to match the subtleties of lies like humor or manipulated media images, which usually require time and labor intensive feature extraction[5]. In contrast, behavior-based approaches work at looking into patterns of spread but are prone to misinterpret content veracity and hence, may be misled by genuine descriptions of user activities [6].
Deep learning has revolutionized the accuracy of fake news detection systems[7]. Transformer models, for which we already have these attention mechanisms are free to be honest. The above-mentioned mechanisms allow the model to focus on important textual features and thus facilitate learning[8]. Numerous studies have shown that the attention layers in transformers can significantly enhance fake news identification accuracy tremendously by tuning of text with key phrase-based processing[9,10]. Data preprocessing is the key to getting better results from the model. The first step of this process is not only to exclude an irrelevant value in the sentences (LOF - Local Outlier Factor) it identifies and removes words that are too far from the topic of the sentence[10,11]. On top of that, model accuracy can

get negatively impacted when the imbalance of classes is an issue[12]. Our research is aimed to tackle this challenge with SMOTE[13], where synthetic samples for minority class are generated that balances minority and majority classes. Fake news detection main problem is the tricky form that misinformation takes and how it can be extremely subtle to fake legit news. Then consider that the datasets used to train detection models are generally class-imbalanced (because quite a bit more news is normal than fake), causing a biased model[14]. This imbalance and requirement that really real be much more accurately classified than the fake articles make it a big problem. The importance of resolving this problem cannot be overstated, since it has a direct impact on the preservation of democratic process, safety of public and information the ecosystems.

Some studies on Detection of fake news have been developed based on analytical approaches from linguistic analysis to network-based methods[15]. Methods in the field of content analyze the text, style and structure of news articles whereas methods based on behavior study what happens to the news and how users engage with this stuff. Deep Learning, especially transformer models, has some new promising ways of tackling context and semantics with performance over common machine learning algorithms in a few cases it conquered. But, many of the existing studies neglect the most important data imbalance problem or not tackling outliers in textual data effectively, which can adversely affect model performance. Furthermore, whilst attention mechanisms at transformers are harvested together very little research on the integration of data preprocessing strategies such as SMOTE and LOF for increasing resilience of model have been studied. This paper is structured as follows: it reviews our work in the context of related research lines and shows how our contribution fills the gaps. Section III is the methodology, implementation of SMOTE for balancing data, LOF for outlier detection and using transformer architecture as a deep learning. Section IV We show the result of our experiments that our mixed approach works In Section V, these results are discussed in comparison with others work and the potential limitations are point out as well as future research directions. Lastly Section VI concludes with a summary of our findings and highlights how this contribution adds value in fake news detection.

Our contributions, we proposed this model after extensively studying the models in previous studies, we found some very important points that were addressed as weaknesses, in some studies as the solution of data imbalance, in other studies there was a lot of training time problems, and some problems with noise. Like all researchers, we aimed to achieve the best results in the shortest time and using advanced algorithms. For this purpose, we designed a new model that has not been designed before, a model that addresses a number of weaknesses in one model. Our research first, checking the datasets to figure out the cause of misleading which is the noise and for this issue we used Local Outlier Factor algorithm also checking the preprocessing innovations and on data imbalance, handling this serious problem with Synthetic Minority Over-Sampling Technique. By proposing a new construct where we combine SMOTE technique with LOF algorithm, one that is original and also different to solve both data imbalance & outlier issues. Making use of this combination potentially helps by balancing the data with synthetic samples generated by SMOTE for minority class and points that lie far from the general pattern of data are outliers as it can find those using LOF. Different, integrated with deep learning transforms and especially attention-transformer model, make the processing and training of the data in a short period of time more accurate and efficient. Our method, by focusing on data preprocessing and balancing instead of other techniques that exist in the literature allows to improve both accuracy and as we use pretrained mechanism which reduce the processing time of fake news detection. With this technique particularly we are directly tackling all the mentioned problems on data imbalance and outliers while benefitting from transformer models to process textual data for a stronger solution on fake news.

2. Related Work

Fake news detection: Initial research mostly depended on natural language processing (NLP) as well as expert opinions to use feature extraction for fake news with limited support from them.

The old methods were lexical analysis, to capture simple textual patterns and have algorithms recognizing lexical features, plus statistical criteria. Specific words frequencies, word-count and sentence constructions are some of the features that researchers analyzed historically to differentiate between fake or real news [7, 16]. Other traditional approaches also tended to rule-based algorithms and early generations of machine learning that were bogged down in the requirement for manual feature extraction coupled with domain expertise merely mitigating constraints to achieve only moderate success in greater generality [8,17].

Moving away from these approaches, some recent studies suggested the implementation of artificial neural networks and deep learning optimizers for fake news detection [18]. The combination of NLP with deep learning is very powerful, it has for instance been proven to significantly improve precision and reduce false positives [1,19],[20]. Deep learning, especially in Convolutional Neural Networks (CNN) and more recently Short-Term Memory (LSTM) networks, has made great strides in complexity detection with the help of accurate features in large datasets and increasing the accuracy and efficiency of recognition models[21,22]. Since transformer models first came out, claiming a turning point — they enable word-level self-attention [23] originally with richer contextual information to be focused on for fine-grained recognition enhancement [24].

BERT and GPT models demonstrated impressive results in many benchmarks [24,25], as consequence of their advanced capability to understand language. Transformers have indeed been observed to increase accuracy and decrease computational time for analysis [26–28].

A part from making deep learning-based system center, researchers have developed methods for coping with difficult in fake news detection challenges like data imbalance [29] and outliers, and so on. To deal with imbalanced dataset some strategies raised in the literature like under-sampling [14], Oversampling and threshold settings. Particularly successful in this area is the creation of artificial samples in the feature space to balance minority classes using the artificial minority oversampling technique (SMOTE) [30,31].

SMOTEBOOST and other adaptive sampling methods have also been explored. The local outlier factor (LOF) has been used to identify anomalies among others [10,32] during the anomaly detection process, thus enhancing the detection.

3. Method and Materials

This method proposes an approach to manage imbalanced datasets to ensure reliability, increase the accuracy of fake news detection through the integration of SMOTE, LOF with transformer-based deep learning. First, the process starts with loading the dataset, which contains both real and fake news, then the necessary data preprocessing is done. Data preprocessing is done to remove noise and useless information and format the data in order to be suitable for modeling.

Therefore, we used LOF (local outlier factor) to identify and remove outliers. This allowed us to find and discard those data points that deviated greatly from the pattern observed in the rest of the data with this algorithm. The fake news dataset was typically unbalanced, so we applied SMOTE (Artificial Minority Oversampling Technique) to the training set only. SMOTE enabled us to generate artificial samples for the minority class (only fake news) artificial samples, which makes the classes use balance for a better training model.

After the data set was cleaned and balanced and worked on with the transformer-based architecture. The architecture is built with feedforward layers, batch normalization and dropout layers that speed up training, help with stability and reduce the variation of internal variables, as well as prevent additions. The model finally obtains a certain amount of fake or real news using the final classifier at the top. Our proposed method improves the accuracy of fake news compared to conventional classification methods. This particular neural network architecture, developed from the transformer model used in this research, is based on AI NLP. Unlike the traditional model, it only has a transformer encoder. Since our goal was to detect fake news, most of the attention was focused on the coder because the textual content needed to be analyzed but no texts were produced. The transformer encoder has layers in each of the two main auxiliary sublayers, which include: multi-head attention and a feed-forward network. Multi-head attention allows the model to focus on different parts of the text simultaneously, which provides a better understanding of complex word relationships. These attention heads take into account the various relationships between these pieces of information and allow the model to use multiple sources of information. Finally, the data is fed into a feedforward network (linear layers and ReLU activation) following multi-head attention to add more depth and complexity to the learned representation of the data.

In order to avoid overfitting and improve the stability of the training, additional techniques such as batch normalization and dropout were added. During training batch normalization normalizes the activation to stabilize learning, to avoid overfitting the Dropout layer usually disables neurons (deactivate neurons randomly during training). This multi-pronged approach enables the Transformer model to analyze text in very fine detail and be able to classify a news story as fake or real.

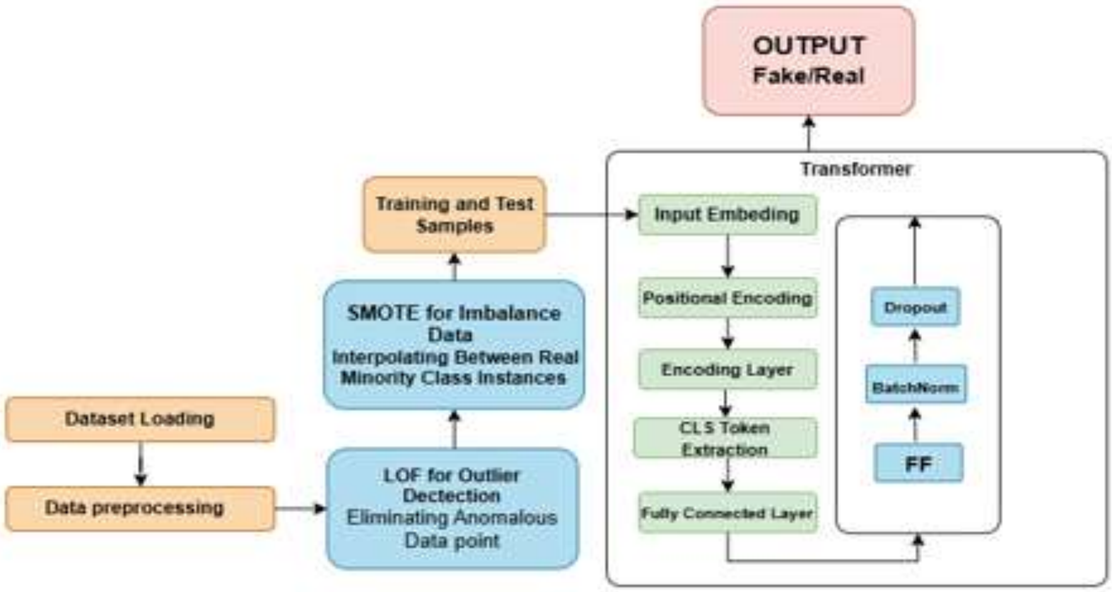

FIGURE 1: The proposed method framework.

A. Input Dataset

For this model the input dataset of news articles or posts probably real and fake. The input data is important for model, because the model with high quality and diverse input will give better result in this stage. Lastly, we make sure the dataset is rich in genres and writing styles, as well as sources in order for the model can be well trained and provides an in-depth analysis and learn all the aspects (top-level) about fake news. Furthermore, properly handle the classes (both real and fake) at this point is important in order to prevent the model to be biased because of class imbalance.

B. Preprocessing the data

This step is important because any text to be trained should be prepared, hence the preprocessing include cleaning the text, this step include several steps: converting every word to lowercase for uniformity, lexical conversion to expand contraction forms for clarity (e.g., "can't" to "cannot"), and anonymization to remove specific individual references (e.g., “@name”) for privacy and content focus. Additionally, punctuation handling was performed to eliminate most punctuation while preserving question marks to maintain inquiry-based sentences, special characters were removed to further clean the text, and stop word filtration was applied to exclude commonly used stop words while retaining critical negations and modal verbs for sentence integrity. The process concluded with whitespace trimming to remove excess spaces and tokenization to segment the cleaned text for computational analysis.

C. LOF for Outlier Detection

A crucial enhancement to accuracy for automatic fake news detection is application of Local Outlier Factor (LOF) for identifying outliers. Outliers may emerge as news which differs drastically from the overall data pattern, i.e., it might be fake news or possibly some data error. LOF locality means the outlier: it finds the data points which are relatively isolated compare in nearest space of neighbor data points in terms of local density. This process helps in removing or replacing with proper data that could trick the model. Following identification, filtering these outliers may improve quality of input data for the transformer model and thus increases the precision in detecting fake news.

Local Outlier Factor (LOF) is a super technique for outlier or anomalies detection in the datasets, which is very useful to find and remove errors or noise [10][32]. LOF is a key player that helps with the quality of training dataset for fake news detection i.e. trains a more accurate model by really fine-tuned detection [25]. It works predominantly at identifying and purging the off-topic words, textual samples which are just noise [7] [24] irrelevant one in text which makes the dataset purer. These steps of preprocessing results in better detection of fake news by guaranteeing that the training data is not only clean but also homogenous.

- Definition of Remoteness

A data point is considered to be LOF data in the LOF method, if the local density of it is significantly less than local densities surrounding neighboring points. Dense is calculated based on the local distance between points and number of neighbors within a given density radius.

- Calculation of the Remoteness Factor

LOF or the remoteness factor of each data point gets computed as the ratio between its local density and mean neighborhood density. LOF for a point p This formula for k nearest neighbors is as follows:

$$LOF_{(k)} = \frac{\sum_{x \in N_{k(p)}} \frac{lrd(p)}{lrd(x)}}{|N_k\ (p)|} \qquad (1)$$

where, lrd denotes the local access density of the point (p), and $N_k(p)$ denotes the set of k nearest neighbors to the point p, $N_k\ (p)$ is the local reachability density of each neighbor x in the set $N_k\ (p)$ and $|N_k\ (p)|$ is the number of neighbors in the set $N_k\ (p)$.

- Noise Detection and Removal

After getting LOF values for all points in the dataset, the points with the calculated values higher than a threshold are identified as outliers and removed from the dataset. Cleaning such outliers is important as they could mislead training data and potentially the model itself.

- Improvement in Model Accuracy

LOF can be used to discard anomalous data, making deep learning models, especially transformer-based models, learn with more effectiveness trough relevant and clean data. Important in the context of fake news detection, where input data quality and precision are what will affect the performance of the model. When those outliers and noise are processed in advance using LOF for preprocessing, it will make model more accurate and efficient as it can only understand key relevant information for better overall accuracy in detecting real news from fake.

D. SMOTE for Data Imbalance

SMOTE is utilized to address data imbalance, a common issue in fake news datasets where real news typically outnumbers fake news. SMOTE aids in balancing the data by generating synthetic examples from the minority class (fake news in this context). This technique operates by selecting examples from the minority class and creating new instances by interpolating between these examples and their nearest neighbors. By training on a more balanced dataset, the model can better identify patterns in fake news and mitigate bias resulting from data imbalance.

This technique (SMOTE) is designed to address the problem of class imbalance in datasets, which is particularly relevant for detecting fake news where a minority class (fake news) may be significantly underrepresented. SMOTE works by creating mixed samples of the minority class, thus balancing the dataset and improving the model's ability to generalize from the minority class [23]. This technique is crucial for enhancing the performance of deep learning models by ensuring that they are trained on a more evenly distributed dataset.

The SMOTE algorithm involves t This technique is critical for improving the performance of deep learning models by ensuring that they are trained on a uniformly distributed data set.

he following steps:

1. **Identify Minority Class**: Determine which class is the minority (in our case, fake news).
2. **Select Minority Samples**: For each example in the minority class, choose its k nearest neighbors (typically $k = 5$).
3. **Create the Synthetic Samples:** For each minority sample, take the difference between the sample and one of its k nearest neighbors, scale this difference with a random real number between 0 and 1, and add it back to the sample. This method creates a synthetic sample in the direction of the minority sample to its nearest neighbor in the line segment.

Formula for Generating Synthetic Samples:

Let x_i Be a role model for the minority class, and x_{zi} be one of its closest neighbors. The new synthetic sample x_{new} is generated as follows:

$$x_{\text{new}} = x_i + \delta \times (x_{zi} - x_i) \qquad (2)$$

where δ is a random number between 0 and 1.

4. **Repeat:** This process is repeated to the desired extent level of balance is achieved between the classes

Our research on improving fake news detection starts by bringing the minority class to balance via synthetic examples for the minority class (fake news) using SMOTE to train our deep learning model, particularly the transformer architecture, which is prone to overfitting on imbalanced datasets. This is essential for reducing bias during training, especially stepping up a notch, the observation features of fake news and with a huge margin of difference in detection accuracy for the system. After effect, we perform data cleaning with LOF. By combining SMOTE with LOF and with deep learning transformations, our method can be considered to tackle the issues associated with quality of data, class imbalance in a comprehensive manner that presents a profound framework for detecting fake news.

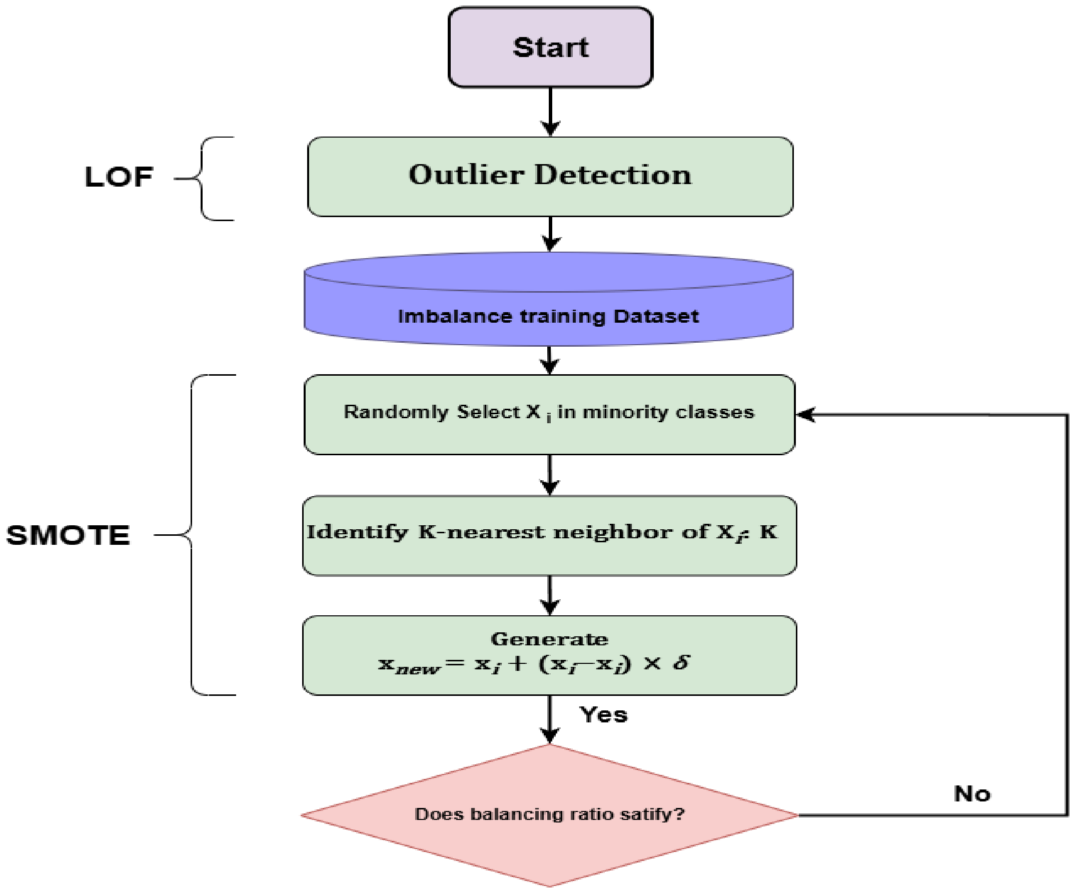

FIGURE 2: LOF-SMOTE Flowchart Illustrate Handling Dataset's Noise and Imbalance.

After collecting the data, the next major step is to split the dataset into training and test cases. The resulting split allows us to measure the performance of our model on unseen data, which generalizes to new cases. Increasing the ratio of training to test data (70-30 or 80-20 is usually chosen as the best general approach) helps to overcome overfitting and have enough data for the model. This step also allows us to use a wide range of validation techniques such as cross-validation to fine-tune the parameters and shape of the model.

E. Transformer Architecture

The transformer architecture is a Deep Learning Model that introduce a new way to handle sequential data without using recurrent neural network, revolutionizing the area of natural language processing. By using self-attention layers, which calculate Display its input and output regardless of sequence order.

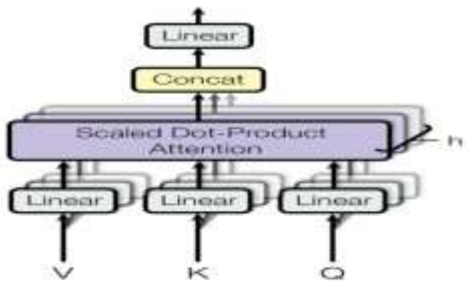

Figure 3: Multi-Head Attention Mechanism[33].

The transformer architecture that we designed have not been designed before, it used in this model for textual feature extraction for fake news detection is a significant point. This arch exploit multi-head attention which focuses on multiple parts of text in parallel, so it is capable of forming more complex relationships between words. The virtue of which makes this model capable of dealing in textual data at the finest level, segregating the simplest differences between real and fake news. The imbedding layer added as first layer inside the transformer followed by positional encoding and dropout layers. An attention mechanism is followed by pooling layer as a multi head-attention layers before the feed-forward network (FFN) which does some more data processing by chaining linear layers and activation functions to perform feature extraction crucial for the classification part.

F. Proposed Model

Below presents the proposed model framework structure:

1. Data Collection Phase: The initial step involves the aggregation of textual content, including sentences or complete articles, from various social media outlets for subsequent analysis.
2. Preprocessing Stage: The gathered text undergoes a cleaning process. This step includes the removal of any extraneous special characters, the elimination of stopwords that could skew analysis, and the conversion of all textual data to a uniform lowercase format.
3. Outlier Detection (LOF): The local outlier factor algorithm is applied to find and remove data points that considerably withdraw from the pattern of the dataset.
4. Addressing Dataset Unbalancing: The Synthetic Minority Over-Sampling Technique (SMOTE) is utilized to address data imbalance, starting by addressing the minority class, then choose its k nearest neighbors to creates a synthetic sample in the direction of minority sample.
5. Training and Testing Samples: splitting the dataset into two sample (Training80% and Testing20%).
6. Transformer Architecture:
   - Input embedding layer: input text will be converted to its numerical representation to produce a vector.
   - Positional Encoding Layer: for each embedded word, a positional encode is added to provide information about its position in the sequence.
   - Encoder layer: the vector is fed to encoder layer this layer consist of multiple identical layers and each has two sub-elements; first Multi Head-Self Attention which weight the importance of different words, to capture the relationships and context. The second Feed Forward Neural Network, higher level features are extracted through attention mechanism.
   - Dropout Layer: this layer randomly set some activation to zero during the training process to prevent overfitting.
7. Classification Head
   - Pooling Layer: aggregate the output from the final encoder layer to form a fixed-size vector, representing the entire input text.
   - Fully Connected (Dense Layer): the pooled vector processed to produce a desire output size.
   - Dropout Layer: to prevent overfitting.
   - Output Layer: final prediction is produced, after applying activation function to produce the final decision (fake or real)
8. Training the Model:
   - Starting training using the training sample dataset.
   - Backpropagation to optimize parameters. Calculating loss function.
   - Setting the epochs till the desired performance.
9. Testing and Evaluating the Model:
   - Testing the model using test samples.
   - Calculating performance metrics.

4. Results and Analysis

A. DATASET OVERVIEW

Our dataset, used for both training and testing the FakeNewsNet which contain two separate subsets on PolitiFact and GossipCop. The subcategories were extracted from PolitiFact veracity claims and GossipCop factchecks. As for PolitiFact, it checks the credibility of political news and assigns articles a label of either "fake" or "real," whereas GossipCop examines entertainment news and assigns that same exact wording. A common characteristic of most fake news articles is an idiosyncratic language pattern. Hence, this work attempts at automatically classifying news stories from only their headlinese, which are taken from PolitiFact and GossipCop training & validation subsets. To be more specific, PolitiFact set has 432 fake and 624 true articles; whereas GossipCop subset has 5323 fake,16817 true[34].

The following table (1) provides a detailed breakdown of the distribution of news articles in the two datasets:

Table 1: Distribution of News Articles in the FakeNewsNet Dataset.

Dataset Name	Dataset Size	Text Genre	Topic Categories/Labels	Annotation Level	# of Annotators	Agreement Measurement
PolitiFact Dataset	21,152 statements	Fact-check Statements	True, Mostly True, Half True, Mostly False, False, Pants on Fire	Statement-level	Experts from PolitiFact	Not specified, relies on expert fact-checking
GossipCop Dataset	2400 articles (40 per domain)	News Articles	Technology, Education, Business, Sports, Politics, Entertainment	Article-level	Manual and crowdsourced	Not specified

This methodical approach allows for a thorough analysis of Identifying fake news using the extensive and diverse data points provided by this dataset.

B. Experiment Setup

The research is experimented on Kaggle's virtual machines (with GPU P100) for the experiments. Kaggle is an online platform that lets user to do data analysis, create machine learning models and focus on solving interesting data science competitions. It provides user side virtual environments that are equipped with super computing resources such as GPU P100 for heavy duty processing and user does not have to invest in his or her personal high-end hardware. PolitiFact dataset (21,152 manually verified statements) used in this study.

C. Metric

We used several important metrics for the assessment of the Models for detecting fake news. This criterion holistically judges the quality of precision, recall and overall model performance. In this study, we used the following measures

1. **Accuracy:** This is simply a measure of how well the model makes its predictions. It is defined as the number of correctly predicted instances (true positives and true negatives) divided by the total instances. Accuracy gives an overview of how well our model performs across all classes.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

2. **Precision:** Accuracy, also known as positive predictive value, represents the proportion of accurate optimistic predictions among all positive predictions made by the model. High accuracy is crucial in the field of fake news detection, as it ensures that the majority of news articles identified as fake are actually fake.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

3. **Recall**: Recall, or sensitivity, measures the proportion of true positives (fake news) that the model correctly identifies. High recall is essential to ensure that most fake news articles are identified.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

4. **F_1-Score:** F_1-Score is the harmonic mean of precision and recall. It is a compromise whereby equal weightage is given both for false positives and for missing positives The F_1-Score is especially handy when class imbalance is present between the classes, which is the case of most fake news dataset.

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

All these metrics capture all the wonders of fake news detection models that are used, in essence covering both their pros and cons separately. The study intends to evaluate the proposed methods for detecting fake news through these metrics in a comprehensive and rigorous way.

D. Results

This study compares different fake news detection models on two datasets derived from the FakeNewsNet collection, namely PolitiFact and GossipCop. Four criteria to evaluate accuracy, precision, recall and F1 score of the model:

- **SAFE (Multimodal)**[35]**:** With a fully connected layer to integrate textual information along with convolutions, pooling layers for feature extraction to sentence-CNN.

- **BERT**[36]**:** Explores bidirectional representations of native text to really understand the downstream context.
- **BERT + LSTM**[37]**:** Using BERT's grasp of context with the sequence modeling nature of LSTM
- **Transformer Attention Mechanism:** Make use of clever attention mechanisms for better contextual and sequential data understanding (the put forward approach).
- **Transformer Attention Mechanism + SMOTE + LOF**: The proposed method uses ADASYN for addressing the class imbalance and LOF is to detect outliers.

The performance of the models on both datasets results as shown in table (2), it is shown that advanced models, namely BERT, BERT + LSTM and the Transformer Attention Mechanism surpass simple models. The best overall performance across the two datasets of the Transformer Attention Mechanism with SMOTE and LOF was proposed.

Table 2: Comparing the performance of PolitiFact and GossipCop models with the results of the proposed method.

Models	Dataset: PolitiFact (FakeNewsNet)				Dataset: GossipCop (FakeNewsNet)			
	Accuracy (%)	**Precision**	**Recall**	**F1 Score**	**Accuracy (%)**	**Precision**	**Recall**	**F1 Score**
SAFE (Multimodal)[35]	87.4	0.88	0.9	0.89	83.8	0.85	0.93	0.89
BERT[36]	86.25	0.9	0.87	0.88	83	0.89	0.89	0.89
BERT + LSTM[37]	88.75	0.91	0.9	0.9	84.1	0.89	0.91	0.89
Transformer Attention Mechanism	89.14	0.92	0.91	0.92	85	0.9	0.92	0.9
Proposed Method “LOF_SMOTE_Transformer”	91.5	0.94	0.93	0.94	87.2	0.92	0.94	0.93

By analyzing Table 2, we can see the performance of the models on two datasets from FakeNewsNet: PolitiFact and GossipCop. For the PolitiFact dataset, the proposed method "Transformer+ SMOTE+ LOF" achieved the highest performance with an accuracy of 91.5%, precision of 0.94, recall of 0.93, as shown in Fig. 3. PolitiFact Comparison Line Graph

Models such as SAFE (Multimodal), the BERT and BERT + LSTM & Transformer Attention Mechanism were evaluated. In GossipCop dataset, the proposed method outperformed all with an accuracy of 87.2%, precision 0.92, recall value as 0.94 and F_1 score of0.93. As shown in Table (2), the proposed method achieved the highest performance across both datasets.

However, it is worth noting that the Transformer model is expected to show improved performance in this particular task, as it is good at long-range dependencies and has context understanding for such fine-grained text analysis as fake news detection. The dataset we use in fake news detection is usually class-imbalanced, and SMOTE (Synthetic Minority Oversampling Technique) helps to overcome this class imbalance problem by combining minority class samples, so it can probably help the model identify some less common fake news patterns. The anomaly detection layer provided by LOF (Local Outlier Factor) makes the prediction more robust and helped us detect outliers or outlier instances that may point to fake news. It combines all of these methods to provide more accurate and robust approach to detect fake news, making it a better performing model versus the other models listed.

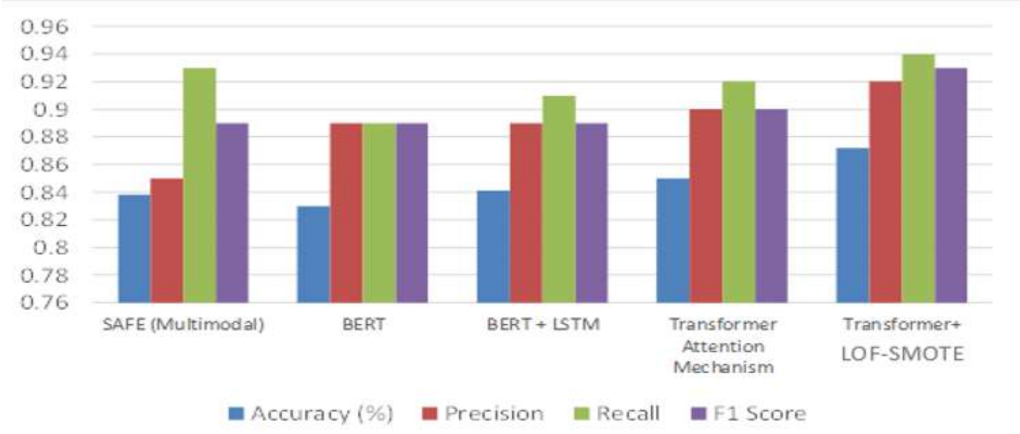

FIGURE 4: PolitiFact Comparison Line Graph.

The performance obtained accuracy with BERT + LSTM was 88.75% and F_1 score of 0.90, conveying nice synergy between deep 2D understanding of context and sequential data processing. SAFE (Multimodal) model had the best performance, accuracy with 87.4% and precision0.9 with high recall (0.89), proposing this model has high efficiency to resolve fake news instances. The figure below shows the performance of Transformer Attention Mechanism, which was followed by BERT + LSTM and SAFE(Multimodal) model. These results are a testament to the importance of NLP techniques and deep learning in improving our ability to detect fake new.

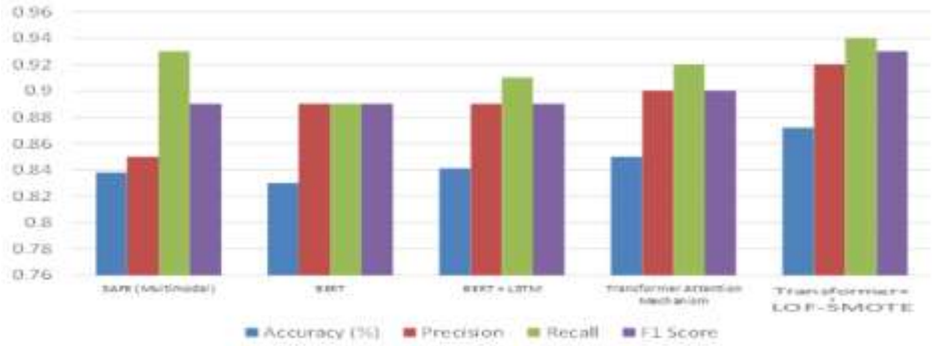

FIGURE 5: GossipCop Comparison Line Graph.

The experiments on GossipCop Dataset confirm the combined of transformation of Transformer Attention Mechanism with SMOT+LOF is the most successful model with an accuracy (87.2%), precision 0.92, recall/recognition 0.94 and F_1 score on this dataset. The reproducible performance across numerous data-sets validates the model to be very general and applicable in various situations. BERT + LSTM was still very good performing with high accuracy at 84.1% and F_1 score of 0.89, showing how adaptable + efficient it can be for different data-sets. in SAFE (Multimodal) achieve high recall (0.72-0.88) and F_1 score (SAFE)089 which further highlight that the approach can struggle with false negatives i.e., missing deceptive content has serious consequences for fake news detection. The figure (4) emphasizes that how Transformer Attention Mechanism with SMOT-LOF performs consistently well in both datasets via the superiority graph representation of the technique across diverse scenarios.

DISCUSSION AND CONCLUSION

Analyzing different models for fake news detection using both datasets shows the efficiency and expandability of implementing deep learning transformers combined with (SMOTE-LOF) are detailed. The results showed that all the advanced model showed high perform across both datasets than traditional ones. An overview of the results of the experiments shows that performance metrics obtained from our proposed method for Fake News Detection are the best, indicating it is best suited in this type of problems. According to experimental result obtained from both datasets, our proposed approach produces better performance metrics, proving that it is appropriate for this kind of issue

Transformer Attention mechanism with SMOTE and LOF: This method outperforms than others across metrics (accuracy, precision recall F_1-score) across both datasets Transformer detections with class imbalance solves by SMOTE and outlier detection with LOF enhancing algorithm's effectiveness for

fake news detection. Bert and Bert+LSTM: these models, successfully capture the importance of context understanding in the domain. In particular BERT + LSTM shows higher performance on complex structured datasets. SAFE (Multimodal): this model, shows higher recall on GossipCop, showing its ability its ability to capture a broader range of fake news instances.
Deep Learning Methods: The superior performances of deep-learning based method like BERT and transformer attention mechanism corroborate the importance of advanced NLP techniques for accurate prediction. Attention Mechanism: The success of attention-based architectures such as the Transformer, dynamically focuses on different parts to explain the fine gradations in fake news. Multi-modal models: SAFE model's high performance, using multimodal strategies to combine textual and other forms of data and indicate that multimodal integration can greatly improve detection performance.
It is important to focus on Models that have a top metric (Accuracy and reminder). The Transformer Attention Mechanism combined with SMOT-LOF is powerful, it requires considerable computational materials. Training and testing these models on various datasets will guarantee strong performance. Investigating new Transformer Attention methods and combining it with hybrid models, also using advanced language processing emerge promising to enhance fake news detection.
This study has comprehensively analyzed the method on how to detect fake news by Using advanced deep learning methods such as Transformers and preprocessing techniques, especially SMOTE for coping class imbalance as well as LOF to tackle outliers Analyzing both PolitiFact and GossipCop datasets prove that our proposed model, combining transformer attention mechanism with SMOTE, achieved significant performance gain over the traditional models on accuracy, precision, recall, F_1. This indicates how using advanced NLP technique is essential to improve the adaptability and reliability for fake news detection system.
While these results highlight some main takeaways: firstly, models need to be versatile, dataset characteristics as we can see from dataset-specific behavior of models, then, attention mechanisms in deep learning models are astonishingly good at breaking down the complicated stories we commonly find in news articles they will play considerable role for properly nuance fact. Finally, the multimodal perspective as shown by SAFE suggests that future work may learn from fusing multiple data types to boost our capacity of detection.
Practically, as a result a framework that we provide to other researchers, beside obtaining higher performance metrics also show robustness via various datasets. Making computational efficiency the best of match, applying fake news detection model on different datasets and trying diverse methods emphasizes a future where the concerned problem may be addressed more correctly and universally. The exploration to improve these models especially on contextual understanding via attention mechanisms and multimodal strategies, as well as researching the next step with stronger and robust detection of misinformation only benefit a more discerning public discourse without being manipulated.

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