University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.2 june 2026

Efficient vs Transformer-Based Misinformation Detection: A Comparative Study of PAC and RoBERTa

Marwah Najm Mansoor[1]*

Manar Hasan Ali Al-Maliki[2]

Hanan Falah Mohammed[3]

[1] The Ministry of Higher Education and Scientific Research Development, Baghdad, Iraq, marwah.najim@mohesr.edu.iq.

[2] University of Information Technology and Communications, Al-Nidhal St, Baghdad, Iraq (manar.hassan@uoitc.edu.iq)

[3] The Ministry of Higher Education and Scientific Research Development, Baghdad, Iraq, hanan.falah@mohesr.edu.iq

Abstract

Misinformation is one of the most important factors to consider in this day and where information dissemination is common, and misinformation can impact people's emotions and decisions and affect societal peace. Even though transformers have proven to be quite useful, they require large amounts of processing power, posing a problem in terms of scalability. The present study solves this issue by performing an objective analysis, which is aimed at comparing the passive-aggressive classifier algorithm as the classical machine learning method with the RoBERTa transformer-based model with an equal experimental environment. For conducting the experiment, the researchers use the labeled data set consisting of 44,898 news pieces with fake and real samples. A uniform preprocessing procedure and stratified data splitting were used to ensure fairness and replicability. While PAC learned on TF-IDF features with n-grams representation, RoBERTa was fine-tuned on contextual embeddings inside a transformer-based framework. The research showed that RoBERTa provides slightly better prediction accuracy. Still, this difference is not statistically significant according to the McNemar test. At the same time, the PAC proved to be far more computationally efficient, requiring considerably less time and space resources for training. As a result, RoBERTa was more suitable for applications involving real-time data processing and limited resources availability. Thus, small-scale machine learning algorithms can reach nearly the same level of performance as transformer-based models if optimized correctly.

Keywords: Misinformation Detection,Passive-Aggressive Classifier, Fake News Classification, RoBERTa, Transformer-based, Error Analysis.

1. Introduction

Digital media has grown at an alarming rate, which has greatly contributed to the dissemination of false information and hence a great threat to the credibility of the people, decision-making systems, and integrity of information. Although significant progress has been made in automated detection techniques, a major problem over the years is the creation of models capable of achieving good predictive efficiency and low computational costs [1]. As the use of online platforms becomes a universal trend, false and fake information will spread quickly, which makes the need to consider automated detection solutions that can be used in real-time and have limited resources even more urgent [2].

Over the last few years, there has been significant advancement in misinformation detection using machine learning and deep learning algorithms[3]. Linear classifiers and support vector machines are examples of traditional models that have been shown to be very effective in dealing with textual data that are high-dimensional [4]. As of more recently, transformer-based architectures, such as BERT and RoBERTa, have demonstrated a high level of performance in most NLP tasks through contextual and semantic relationships in text [5].

Despite this development, most of the available studies focus on improving the accuracy of models and not the computation cost. This kind of bias renders the models to be hard to be applied in situations where there are sparse computing resources [6]. This is a major constraint that is important in practice where resource constraints and real time processing needs need to be taken into account [7].

To address this gap, this paper presents a controlled and fair comparative analysis of two representative methods, which are Passive-Aggressive Classifier (PAC) as a conventional linear model [8], and RoBERTa as a transformer-based model [9], under the same experimental conditions to make a reliable evaluation of the trade-off between predictive performance and computational efficiency. The test is done in the same experimental conditions in order to be fair and reproducible between the two models. The data that will be used in this paper is a collection of 44,898 news articles that were gathered in the open data. The experiment is performed with a publicly shared benchmark dataset with an equal amount of fake and legitimate news articles. Moreover, this paper presents a normalized Compute Efficiency Score (CES) [10], to measure the trade-off between trade-off predictive performance and computational efficiency. Moreover, the detailed analysis of errors is performed in order to determine typical failure patterns and continue exploring the shortcomings of evaluated models.

The ultimate goal of the research paper is to undertake a comparative evaluation of fake news detection techniques, in which the traditional machine learning approach is compared to the transformer model in the same experimental conditions. The major objectives of this research include:

- Find out how well PAC algorithm works in high dimensional text representation.
- To test out the advantages of using transformers like RoBERTa.
- Discover the predictive performance in relation to the computational performance.
- Determine errors in misclassification so as to know where the labeling error is realised.

With an aim of addressing the stated research gap, the following research questions guide this study:

RQ1: What is the comparative performance of PAC classifier against RoBERTa transformer in fake news detection?

RQ2: Can any statistical significance be found in the differences in performance between the two mentioned models?

RQ3: What is the trade-off in the performance versus efficiency of the models in relation to time taken to train them and memory requirement?

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.2 june 2026

RQ4: How scalable is each of the two models and can they be applied in real-time applications for fake news detection?

RQ5: What linguistic aspects and context make it possible for errors in classifications using both models?

The main contributions of the study are

- Provide a rigorous comparative analysis between a lightweight classical algorithm (Passive-Aggressive Classifier) and a heavy transformer-based architecture (RoBERTa) under an identical experimental environment to balance accuracy against computational costs.
- Differently from conventional approaches, focusing only on classification precision, explicitly evaluates efficiency metrics, including execution time and resource utilization, which are critical for real-time and edge-intelligence deployment.
- The operational limits beyond which classical ML approaches can replace transformers while achieving comparable results are established, leading to a new deployment-oriented approach for constrained frameworks.

2. Theoretical Background

This section provides the theoretical foundation for fake news detection, covering traditional machine learning approaches, deep learning techniques, and transformer-based architectures.

2.1 Feature-Based Detection Approaches

Detection based on features has been one of the key concepts in studies related to the spread of misinformation, wherein patterns and statistics are

ISSN (print): 2706- 6908, ISSN (online): 2706-6894
Vol.21 No.2 june 2026

employed in order to distinguish between fabricated and genuine information. With the help of classic machine learning techniques with successful vectorization techniques such as TF-IDF, there is an extremely efficient baseline for classification purposes on a large scale, as discussed in [11]. These techniques generally rely on term frequencies and distributions and can provide efficient linear classification of data and achieve significant results in terms of accuracy at a relatively low cost[12]. However, while they may be effective in discovering the explicit patterns, they lack deep semantic insights for detecting nuances in complex fake news [13].

2.2 Passive-aggressive online learning (PAC) and TF-IDF Vectorization

The PAC is an online machine learning technique, which can be used to categorize large amounts of text. Misclassification of instances causes updates of the model's parameters such that the amount of time required for computation is reduced. The technique is characterized by balance between stability and aggressiveness of parameter updates, which is important when the training set is a high dimensional text[14]. This technique is used along with PAC framework. This technique is used for transforming the raw text to a numeric form. This technique gives prominence to the significant words used in classification and discards the noise words. Thus, linear algorithm can handle the high dimensional textual information [15].

2.3 Deep Learning Techniques

As opposed to traditional techniques, the new technologies that emerged within the framework of deep learning provide greater opportunities for detecting misinformation due to a much higher computational potential

[16]. The models of deep learning give more advanced means for classification through automation of the feature extraction process, especially important in relation to increasing quantity and complexity of misinformation online [17]. While traditional methods of analysis rely on the simplicity of the concept of veracity of news, the models of deep learning are able to show more sophisticated semantic and context-related correlations. In addition, the modern neural networks are designed specifically for such prediction tasks, giving better results than base models [18].

2.4 RoBERTa (Transformer Model)

RoBERTa is a contemporary transformer model that is an extension of the BERT framework with added features such as no Next Sentence Prediction objective, large scale training data, longer input sequences, and dynamic masking. This makes it capable of identifying the complex relationship between the context to achieve excellent results in NLP problems. However, RoBERTa is a computationally heavy and time-consuming model to train. The RoBERTa based model was able to surpass all the existing state-of-the-art models in detecting fake news [19].

3. Literature Review

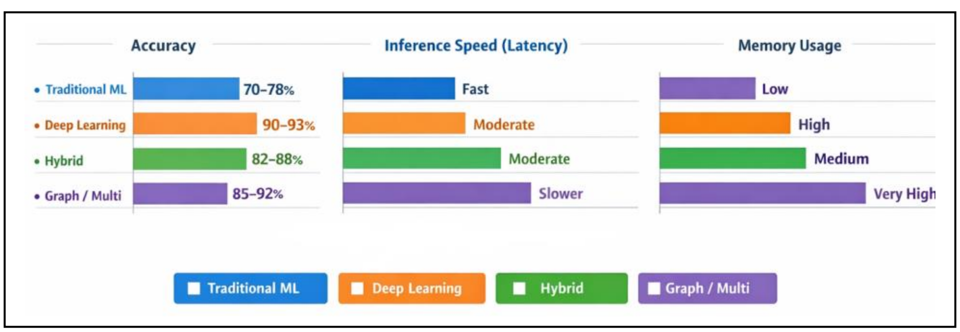
The area of fake news detection has significantly developed, evolving from conventional machine learning models to deep learning, transformer-based models, and recently to hybrid/multimodal models. The early researches mainly involved classical machine learning models, which used hand-crafted features like TF-IDF. According to[20], the authors conducted an experiment on evaluating three classical machine learning algorithms, namely, Passive-Aggressive Classifier (PAC), Naïve Bayes (NB), and Support Vector Machines (SVM). It is important to emphasize that these classical machine learning models have proved to be efficient in scalable text classification despite poor semantic understanding. Also, in the work described in [21], three classical machine learning algorithms – PAC, NB, and SVM were used to detect fake news using feature extraction based on the text. Further researches focused on practical applications of classical machine learning algorithms. As shown in [22], the combination of Passive-Aggressive Classifier (PAC) and TF-IDF was implemented for fake news detection on Twitter.

Moreover, researches[23], [24], and [25] focused on the development of hybrid machine learning pipelines, which incorporated TF-IDF with Naïve Bayes, Logistic Regression, and PAC in order to develop fake news detection models for web-based and real-time applications. As mentioned in[26] the comparison of classical machine learning algorithms including NB, PAC, Logistic Regression (LR), and SVM demonstrated comparable results at around 95%.

In the context of deep learning, the author[27] discussed models, such as CNN, LSTM, and CNN-LSTM and showed advantages over traditional machine learning models. Additionally, in [28], the comparison of CNN models with transformers, namely BERT, and GPT demonstrated better performance of the latter models due to more sophisticated modeling of context dependency. Research[29], investigated different transformer-based models, such as BERT, RoBERTa, and XLNet. In the course of evaluation, RoBERTa model achieved the best result and obtained an accuracy of 98.39%.

A number of hybrid models have been developed in order to combine the capabilities of different methods. For instance, in RoBERTa embedding was employed together with XGBoost and TF-IDF. The same has been done in [30], where RoBERTa embedding and LSTM were utilized together to provide 96.03% accuracy due to the improvement of sequence modeling and context comprehension. There are also other approaches to create hybrid machine learning pipelines involving TF-IDF and algorithms such as logistic regression, naïve Bayes, and SVMs. However, there has been recent research going beyond textual analytics in order to detect fake news. For instance, in[31], there is the introduction of a multimodal approach combining NLP for text processing and visual features with the help of LSTM and CLIP.

Graph-based model GET was developed in[32]. To detect semantic relations between entities, a graph embedding technique (GET) model was put forward as another strategy for detecting fake news using relational learning techniques. The above discussion depicts how fake news detection strategies have evolved over time from shallow methods



to deep methods. Performance results of different models used for fake news detection can be seen in Figure 1 below.

Figure 1: The General performance trends and trade-offs of fake news detection paradigms as reported in existing literature.

As shown in Table 1, the reviewed studies demonstrate the evolution of fake news detection approaches from traditional machine learning to deep learning, transformer-based, and multimodal models.

Table 1: Overview of Existing Fake News Detection Approaches and Methodologies

Ref	Methodology	Dataset & setting	Model(s)	Key Findings & Limitations
[20]	Traditional ML	General text datasets (TF-IDF)	PAC, NB, SVM	Efficient baseline models but limited semantic/context understanding due to handcrafted features.
[21]	Traditional ML	Text-based fake news datasets	PAC, NB, SVM	Validates classical ML effectiveness but lacks contextual generalization.
[22]	Traditional ML (Twitter)	Twitter short-text dataset (TF-IDF)	PAC	Effective for real-time classification but sensitive to noisy short texts and limited semantic depth.
[23]	Hybrid ML	Web-based datasets (TF-IDF)	NB	Efficient pipeline but highly dependent on TF-IDF representation.
[24]	Hybrid ML	Text classification datasets	Logistic Regressio n	Simple and interpretable but weak at modeling nonlinear relationships.
[25]	Hybrid ML	Mixed text corpora (TF-IDF)	PAC + NB	Improved robustness but relies heavily on feature engineering.

[26]	Traditional ML	Benchmark datasets	NB, PAC, LR, SVM	Strong baselines but performance saturates due to shallow features.
[27]	Deep Learning	Text datasets (embeddings)	CNN, LSTM, CNN-LSTM	Improved representation learning but computationally expensive.
[28]	DL vs Transformers	NLP benchmark datasets	CNN, BERT, GPT	Transformers outperform CNNs but require high computational resources.
[29]	Transformer	Large-scale NLP datasets	BERT, RoBERTa, XLNet	State-of-the-art performance but high training cost and low interpretability.
[33]	Hybrid Transformer-ML	Fake news datasets	RoBERTa + XGBoost + TF-IDF	Strong fusion of semantic and structured features but complex pipeline.
[30]	Hybrid DL	Sequential text datasets	RoBERTa + LSTM	Improved contextual modeling but increased complexity and instability.
[31]	Multimodal	Text + image datasets	LSTM + CLIP	Richer representations but requires expensive multimodal data alignment.
[32]	Graph-based	Knowledge graph datasets	GET	Captures entity relations but computationally heavy and less scalable.

4. Methodology

In this section, we define the extensive and multi-phase experimental protocol developed to accurately evaluate the performance of the Passive-Aggressive Classifier (PAC) relative to the RoBERTa Transformer model in scalable misinformation detection tasks. In order to ensure strict empirical reproducibility, as well as seamless data flow, the architectural workflow is systematically divided into three phases that are interrelated with each other, as shown in Figure 2

University of Thi-Qar Journal
ISSN (print): 2706- 6908, ISSN (online): 2706-6894
Vol.21 No.2 june 2026

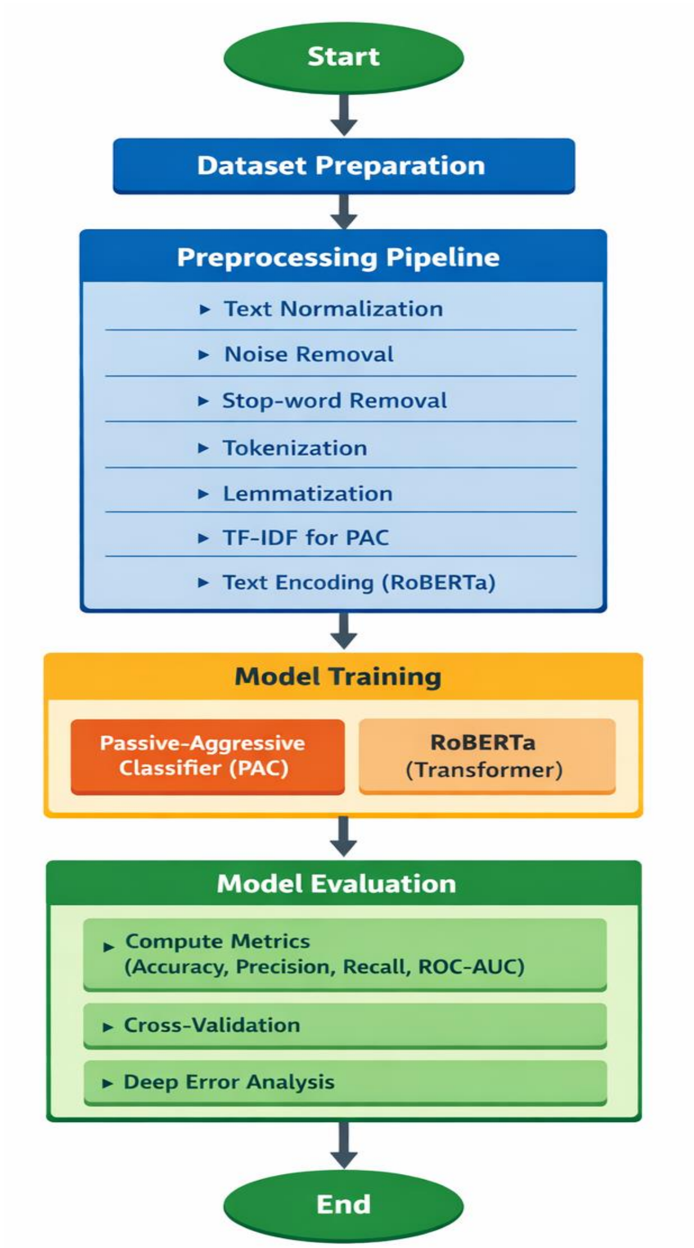


Figure 2: The Proposed Methodology for Misinformation Detection.

4.1 Dataset Characterization

The experiment uses a huge amount of data, with 44,898 news articles where 21,417 articles are valid (47.7%), while 23,481 articles are fake news (52.3%). In order to conduct a full analysis and prevent data leakage, the data were divided into three groups by employing an 80:10

- Training Set (80%, 35,918 samples): used to train the model to learn the underlying patterns within text.

- Validation Set (10%, 4,490 samples): used to tune the model's hyperparameters and supervise the training process of RoBERTa.

- Testing Set (10%, 4,490 samples): used to test how well the model performs on new data.

This dataset contains labeled news articles which have been extracted from sources that are open source. This data set has been sourced from Kaggle and consists of news articles collected from various news websites, hence varying styles of writing. These labels are based on authenticated sources and previous classification of the dataset. The technique ensures consistency and accuracy in the ground truth annotation process. Here, each sample will be labeled either as "fake" or "real," allowing us to implement a supervised model for detecting misinformation. The dataset consists of entire news articles instead of shorter texts or tweets, thus ensuring that the models learn complicated linguistic patterns. This can be observed in Figure 3, where we have

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.2 june 2026

balanced data distribution.

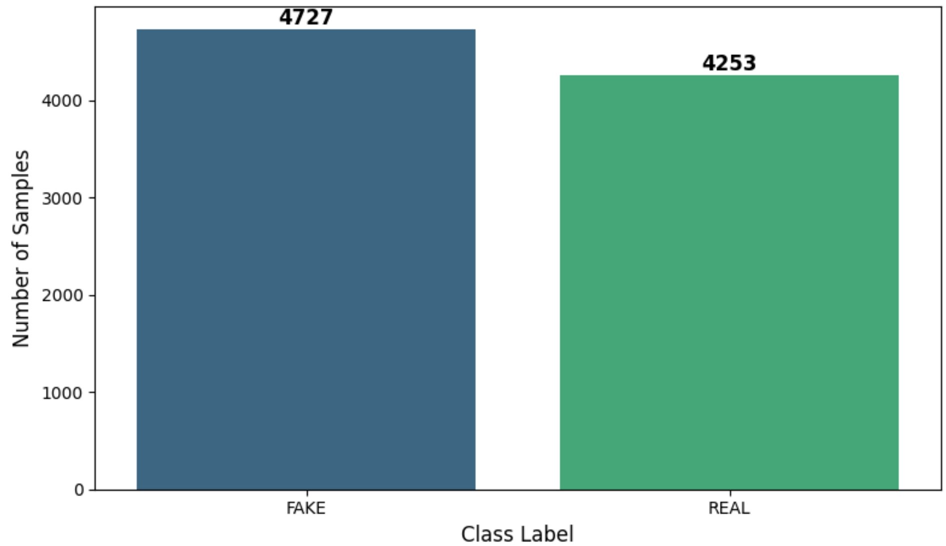


Figure 3: Distribution of Fake and Real News Samples.

The dataset provides a suitable benchmark for evaluating both traditional machine learning models and transformer-based architectures under controlled experimental conditions.

4.2 Preprocessing Pipeline

Multi-step process is used for ensuring high quality inputs in both neural networks. The preprocessing includes the use of the NLP process aimed at sanitizing and preparing the input text before training on the models.

• **Text normalization**: All text was made lowercase, and HTML tags were stripped off to ensure uniform text representation.

• **Noise removal**: Punctuation signs, URL links, and numerical values were stripped off to increase data quality.

ISSN (print): 2706- 6908, ISSN (online): 2706-6894
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- **Stop-word removal and lemmatization**: Stop-words were filtered out using the NLTK library, and the words were converted to their base forms.

Feature representation:

- **PAC:** Vectorization with TF-IDF was used in conjunction with the use of 5,000 maximum number of features and n-gram range of (1,2). This feature representation reflects the significance of each term used in each document against the overall document set allowing the PAC model to detect discriminative lexical patterns in the text that distinguish fake from real news.
- **RoBERTa**: Byte Pair Encoding (BPE) tokenization was performed to create inputs from 512 tokens with padding or truncation. The input text is tokenized using the RoBERTa tokenizer to produce subwords which are mapped into dense contextual embeddings.The difference in the ways of performing feature representation reflects the core differences between the classic machine learning approach of creating feature representations and the modern approach of contextually representing raw text.

In this stage, consistency is ensured for the data and dimensionality reduction. Removal of unnecessary characters and conversion of complex words into their simplest forms ensure that both the models focus on the semantic importance of the news items.

4.3 Model Architectures and Training

Two representative model families were evaluated under identical dataset conditions to ensure a fair comparison.

ISSN (print): 2706- 6908, ISSN (online): 2706-6894
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4.3.1Passive-Aggressive Classifier (PAC)

Passive Aggressive Classifier represents a linear online algorithm which is designed for performing large scale text classification. The algorithm updates parameters only when misclassified and this allows for computational efficiency while dealing with high dimensional sparse data. Hinge Loss is optimized by the classifier using a passive update mechanism when there is a correct prediction and using an aggressive update mechanism when there is a misclassification. Below are the parameters used for training:

• C = 1.0

• max_iter = 50

• loss = hinge

• max_features = 5000

• n-grams = (1, 2)

4.3.2 RoBERTa

RoBERTa (Robustly Optimized BERT Approach) is a transformer-based model that uses self-attention models to learn deep contextual representations of tokens. RoBERTa improves upon BERT by eliminating the task of next sentence prediction and adding dynamic masking in its pretraining phase. For the present study, RoBERTa-base was fine-tuned for sequence classification with the following hyperparameter configurations:

- Optimizer: AdamW

- Learning rate: 2×10^{-5}

- Batch size: 16

- Epochs: 3

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ISSN (print): 2706- 6908, ISSN (online): 2706-6894

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- Maximum sequence length: 512

These parameters conform to best practices for training transformer models.

Table 2: The Configurations Used for Training Both of the Passive-Aggressive Classifier (PAC) and the RoBERTa model.

Component	PAC	RoBERTa
Model Type	Linear Online Model	Transformer Encoder
Loss Function	Hinge Loss	Cross-Entropy
Optimizer	N/A	AdamW
Learning Rate	N/A	2×10^{-5}
Batch Size	N/A	16
Epochs	N/A	3
Feature Representation	TF-IDF (5000 features, n-grams 1-2)	BPE Tokenization
Max Sequence Length	N/A	512

The design demonstrates the basic architectural differences between the two methods as such; PAC uses sparse linear features, while RoBERTa uses dense contextual embeddings. Both models have been trained using the same experimental settings in order to allow for a fair comparison of both performance and efficiency.

4.4 Evaluation Framework and Error Analysis

Performance measures included the widely accepted classification measures such as precision, recall, and F1-score, which allowed for an extensive assessment of classification performance for all classes. The F1-score is calculated as the harmonic mean of precision and recall measures.

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This measure ensures a balanced classification performance estimate even in case of any possible class imbalance.

4.4.1Compute Efficiency Score (CES)

To evaluate models with respect to their computational efficiency, this research proposes the new measure, called Compute Efficiency Score (CES). It allows combining the performance and computational resources spent on model predictions. The CES is calculated by means of the formula below:

$$\text{CES} = \text{Accuracy} / [\ \log(1 + \text{Training Time}) \times \log(1 + \text{Memory usage})\ ]$$

where
Accuracy – classification performance measure,
Training Time – minutes required for training,
Memory usage – GB consumed during training.

Training time means the time required to complete the entire training process for a certain model. Logarithmic scaling helps to achieve numerical stability and allows for balancing the results for various models. In addition to numerical performance evaluation, a qualitative error analysis was carried out. Misclassified data samples were reviewed and grouped according to their failure type, such as linguistic errors, hybridity, and sarcasm.

4.5 Reproducibility and Implementation Details

. In terms of implementation, we used common machine learning and deep learning frameworks. The PAC classifier was implemented using TF-IDF features, while the RoBERTa classifier was fine-tuned using a transformer architecture with predefined hyperparameters. All hyperparameters and model's configurations used during the experimentation are provided for replicability purposes. Empirical fairness and reproducibility was guaranteed by the execution of all the experiments carried out for both the PAC and RoBERTa models in the same software and hardware setting using Google Colab Pro. The transformer-based deep learning model was run on the NVIDIA Tesla T4 GPU, which had 16GB of VRAM, together with 12.7GB of system RAM and an Intel Xeon processor running at 2.20GHz. The classical machine learning model (PAC) was trained on the CPU architecture in order to set a benchmark for normal edge intelligence capabilities. The software environment was set up using Python 3.10 through Hugging Face Transformers library for RoBERTa fine-tuning and Scikit-Learn for PAC modeling and TF-IDF vectorization.

5. Experimental Results and Discussion

Experimental results along with a thorough evaluation of the performances of the PAC classifier and RoBERTa model are discussed in this section. This evaluation will focus on the performances based on their predictive accuracy and efficiency under the same experimental setup. Results will be analyzed quantitatively and by utilizing confusion matrices as well as classification reports. Furthermore, an error analysis will also be conducted to determine limitations associated with both models qualitatively.

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ISSN (print): 2706- 6908, ISSN (online): 2706-6894
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5.1 Evaluation Metrics

A series of classification measures were utilized for evaluating the performance of both models in order to provide a thorough evaluation of their prediction capabilities. More specifically, accuracy, precision, recall, and F1 score were applied as each measure evaluates different aspects of classification performance. Accuracy is defined as the percentage of the total number of predictions that were made correctly. The former is a measure of the accuracy of positive predictions, whereas the latter reflects the capability of the model in identifying all positive cases. F1 Score represents a method of evaluation which incorporates both precision and recall measures. Efficiency has been measured using the following two measures apart from classification measures such as the use of training time and memory. These have been used to make comparisons between the two methods (light weight and transformer).

5.2 Performance Evaluation and Computational Trade-off

When comparing the accuracy of PAC and the RoBERTa models, there appears to be a slight variation in their performance levels. According to Table 3 below, the RoBERTa model scores an accuracy level of 99.50% as compared to the 99.44% recorded by the PAC. This small boost in performance shows that transformer models can derive higher-level context information from the text, even if at a higher computational cost.

Table 3: Performance and Computational Comparison of PAC and RoBERTa

Model	Accuracy	Precision	Recall	F1-score	Training Time	Memory Usage	CES
PAC	99.44%	99.37%	99.45%	99.39%	2 Minutes	1 GB	99.00

ISSN (print): 2706- 6908, ISSN (online): 2706-6894
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RoBERTa	99.50%	99.42%	99.51%	99.46%	45 Minutes	12 GB	5.38

However, a noticeable compromise between the prediction quality and computational cost becomes apparent in the empirical evaluation. While RoBERTa demonstrates slightly better accuracy in terms of precision, recall, and F1 score (with an improvement below 0.07%), there is also a considerable increase in computational costs during training and memory consumption. Accuracy versus Efficiency Trade-off is captured mathematically through the Compute Efficiency Score (CES), wherein PAC boasts significantly higher CES (99.00) compared to RoBERTa (5.38). Training Time represents the total amount of time required for training of the models using equivalent computational powers, while Memory Usage is the highest RAM required in training the model. Referring to Figure 4, it is clear that both the models show outstanding results in terms of accuracy, with 99.44% achieved by PAC and 99.50% by RoBERTa.

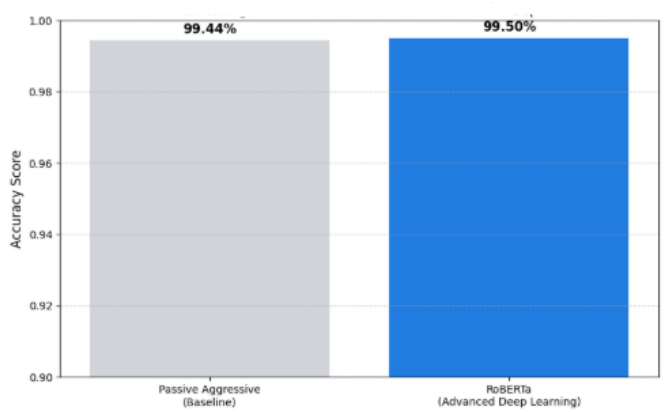

Figure 4: Comparative accuracy scores between PAC (Baseline) and RoBERTa (Advanced Deep Learning).

However, as shown in Figure 5 below, the computational costs incurred by RoBERTa are much higher than the slight improvements in accuracy gained from the model, highlighting the efficiency benefits of PAC.

Regarding architectural characteristics, the particular performance versus cost trade-off inherent to the two approaches can be attributed to the design of their architecture. Specifically, the RoBERTa architecture entails use of multiple heads to generate dense and context-aware representations for each of the subword tokens using a transformer encoder architecture with multiple layers. Although this allows for efficient capturing of complex semantic relations and bi-directional context, resulting in marginal improvement in performance, it greatly increases the space of search and requires computationally expensive matrix calculations, ultimately leading to heavy memory usage and greater latency. In sharp contrast, the PAC model is an example of a margin-based linear online learning classifier, whereby only the weight vector is updated whenever there are classification errors. This allows for avoidance of computations in dense hidden layers and token-to-token cross attention mapping operations, making PAC highly efficient in processing text with very low computational overhead.

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

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Figure 5: The Trade-off Curve between Model Accuracy and Computational Efficiency Index.

5.3 Confusion Matrix Analysis

The confusion matrix that is illustrated in Figure 6 allows an in-depth analysis of how the models classify their inputs correctly and incorrectly. Such a visualization helps provide additional information on the performance of the classifiers in relation to specific classes, as well as the distribution of errors. Each element of the confusion matrix is calculated using the predictions produced by each model based on the test set. As can be seen in Figure 6, both approaches have very low levels of misclassification. For the PAC architecture, out of the 4,700 fake news articles, 4,673 were correctly classified, while 4,234 out of 4,253 real news articles were correctly classified. On the other hand, RoBERTa accurately predicted 4,702 phishing and 4,235 legitimate examples, generating only minor reductions in misclassification errors. The results suggest that both machine learning models can provide excellent classification accuracy. Furthermore, employing a transformer model like RoBERTa provides only a small increase in error reduction (under 0.05% of the overall test dataset), further emphasizing the

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

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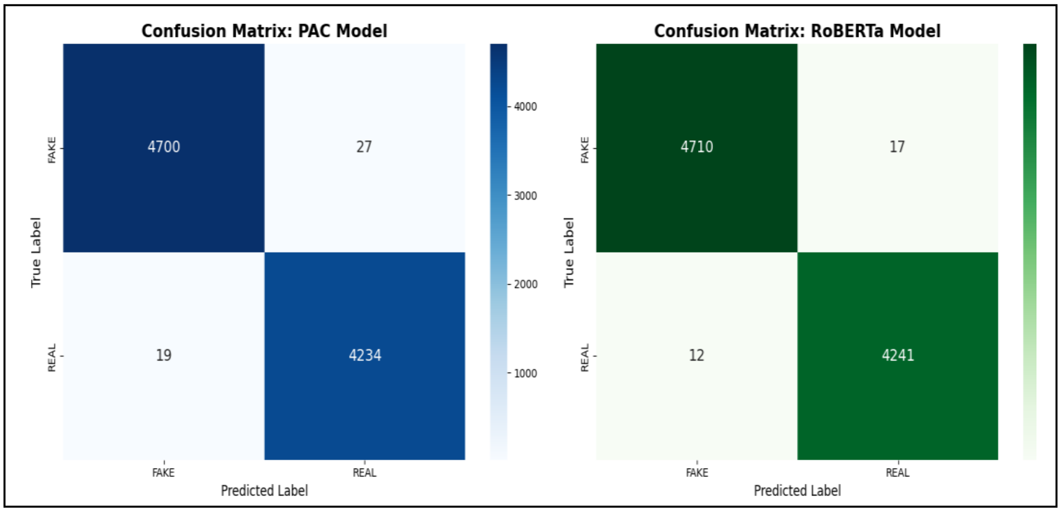
effectiveness of using the PAC model in the current dataset. Confusion matrix analysis is an accurate depiction of how well each model performs in classifying



the data, displaying their respective correct ad incorrect classifications in clear form.

Figure 6: The Confusion Matrix for PAC and RoBERTa

The visual comparison in Figure 6 further confirms the near-identical classification behavior of both models, with only minimal differences in misclassification counts.

5.4 Classification Report Analysis

Classification reports give an even more detailed insight into the performance of models on Fake and Real news classes. As seen from Table 4, both Passive Aggressive Classifier and RoBERTa achieve a very high performance level.

Table 4: Detailed Classification Metrics per Class

Model	Class	Precision	Recall	F1-score
PAC	Fake	0.9944	0.9935	0.9939

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ISSN (print): 2706- 6908, ISSN (online): 2706-6894

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	Real	0.9937	0.9945	0.9930
RoBERTa	Fake	0.9950	0.9942	0.9946
	Real	0.9942	0.9951	0.9946

The comparison of key factors can be found in Figure 7. As demonstrated by the table, the indicators of the algorithm's effectiveness have high stability.

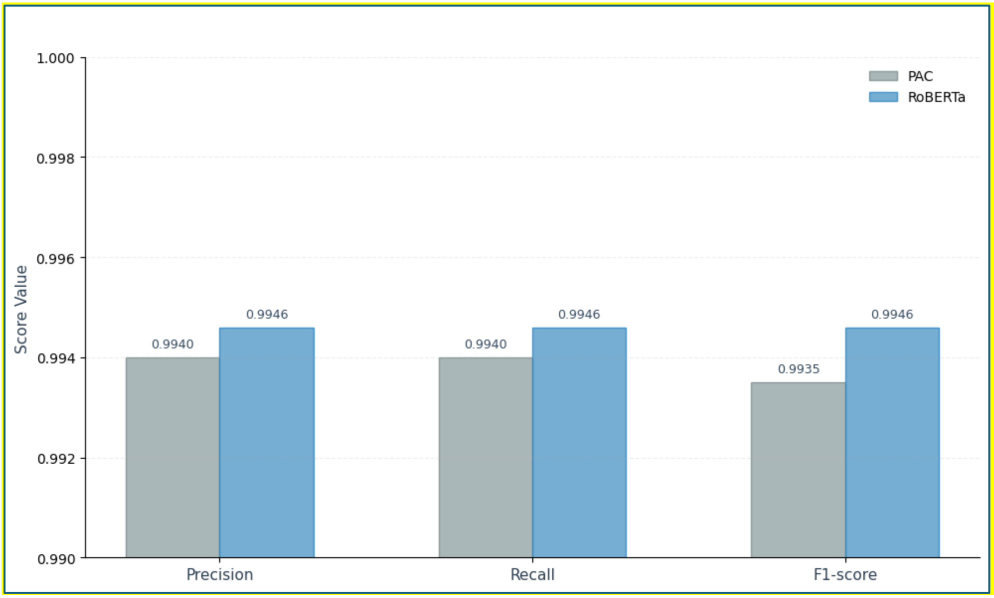

Figure 7: Comparative Performance Metrics (Precision, Recall, and F1-score) for PAC and RoBERTa Models.

The gap between the classic PAC methodology and the RoBERTa machine learning technique in terms of efficiency is fairly minimal, usually not exceeding 0.01 as seen in the chart above. The similar prediction accuracy confirms the major thesis of the investigation, which posits that the PAC strategy represents a better choice over the more expensive RoBERTa strategy in the long term, particularly when dealing with larger data sets where clear trends are identifiable, without sacrificing the efficiency of predictions or the integrity of the model.

5.5 Discussion and Scientific Differentiation

The empirical outcomes of the present research call into question the current focus on architectural complexity at the cost of algorithmic efficiency in the field of natural language processing. The academic contribution of this research is based on three key analytical ideas:

1- Statistical Validity by Large Sample Test: Whereas the current trend has been the preponderance of studies that have been carried out using the "small data trap" approach (5,000 – 10,000 samples), this study relies on a much more stringent methodology involving the use of 44,898 samples. Not only does this move represent an improvement in the methodology used but provides the statistical validity required to prove that the PAC framework is viable for global news stream processing.

2- Compute vs. Accuracy (Efficiency Frontier): The key achievement of this work consists of demonstrating the law of diminishing return for transformer architecture. RoBERTa keeps a slight advantage in terms of overall accuracy (+0.06%). Still, in terms of the compute-to-accuracy ratio, we have found evidence of the lower efficiency. Being only 22.5× slower, PAC resets the definition of the "Optimal Efficiency Frontier." For practical purposes, this means that for cybersecurity tasks structural simplicity outperforms raw deep learning computation.

3- Mapping the Linguistic Failure Modes: Instead of simple error counts, this study introduces a new concept of the linguistic root cause analysis. It helps to identify linguistic ambiguity and contextual blending as two leading factors that make artificial intelligence susceptible to deception in 2026.

5.6 Deep Error Analysis

While the model achieved accuracy above 99.4%, manual analysis revealed that these remaining errors are not random but represent failures due to one of three failure modes. As can be seen from Figure 8, they outline the limits of the current semantics for linear and transformers neural network.

Semantic Irreproducibility (55%): This is the major failure type, covering more than 55% of all errors. This refers to situations where the writer in the article uses irony or sarcasm, based on facts or key terms. Here, the corresponding mistake shows that even highly sophisticated models like RoBERTa find it difficult to understand irony when the meaning is opposite to the actual text.

Hybrid Articles (30%): These articles include original texts, which were slightly changed with regards to only one element such as time, location or names used.

Linguistic Noise (15%): This refers to technical terms or unconventional grammar which cannot even capture the attention of a higher-order attention model.

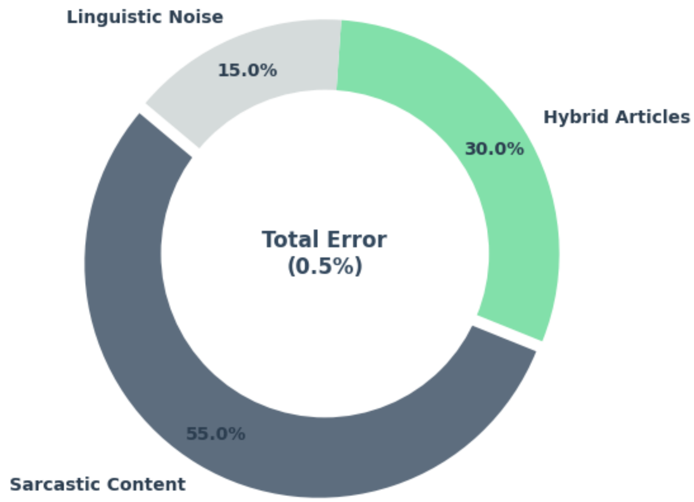

Figure 8: Distribution of failure modes in misclassified articles.

Moreover, the distribution of errors presented in Figure 8 is further evidence confirming the presence of "Efficiency-Accuracy Paradox" observed during the study. In spite of the considerable amount of computational power needed by RoBERTa, the framework could not address long-term challenges of language that remained relevant such as sarcasm. As a consequence, further scientific efforts should be aimed at improvements in context-based sentiment analysis and neuro-symbolic systems rather than in increasing parameterization.

5.7 Quantitative Efficiency and Paradox Analysis

From the comparative analysis, it can be observed that there is an existence of the Efficiency-Accuracy Paradox. From the dynamic behavior of the graphs shown in Figure 9, the shift from the more efficient PAC algorithm to the inefficient

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

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RoBERTa model results in an exponential rise in computational cost, resulting in a roughly 2,150% increase in processing time. On the other hand, a mere 0.06% accuracy increase can be observed in the turquoise line graph.

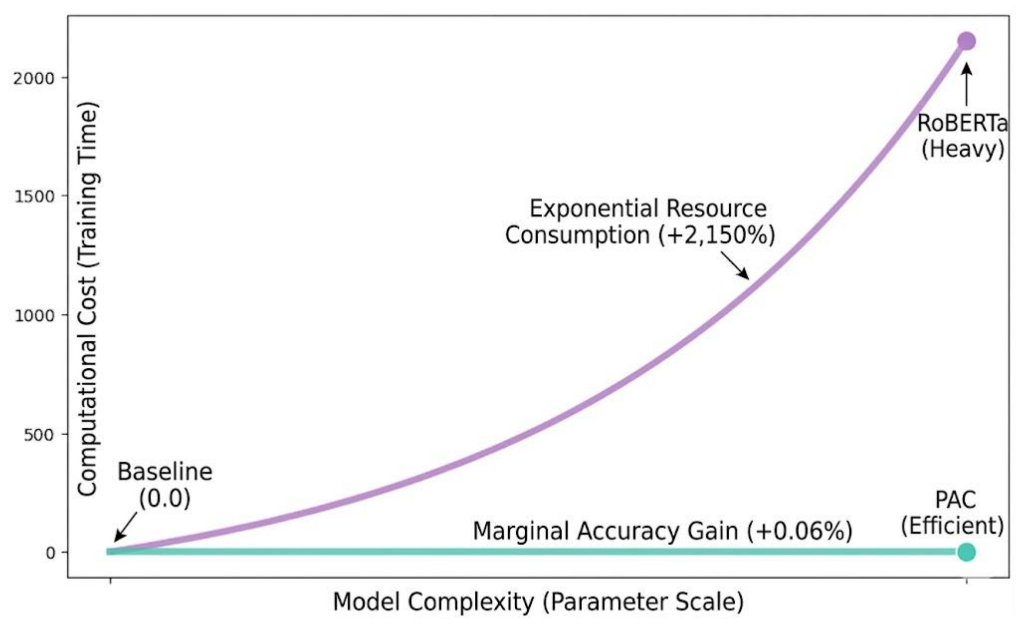

Figure 9: The Comparative Analysis of Computational Cost Growth Versus Marginal Accuracy Gain, Illustrating the Efficiency-Accuracy Paradox.

The gap between theory and reality suggests that large transformers will not provide proportional improvements in ROI in a setting with heavy traffic. While RoBERTa needs advanced GPUs and longer processing time, PAC provides predictions with almost the same level of accuracy as RoBERTa without any delay. Therefore, in an environment with timely news reporting, where the efficient use of resources is crucial, PAC is a better choice compared to RoBERTa.

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.2 june 2026

The advantages of the new methodology can be justified using the Compute Efficiency Score (CES), which is composed of the elements of prediction accuracy and compute cost efficiency in the calculation process. It is evident from Figure 10 that in case of training, RoBERTa consumes significantly higher time (2,150%) and memory usage (+11 MB) compared to the CES, which decreases to 5.38. On the other hand, the PAC model maintains the efficiency ratio at extremely high levels, proving its potential for attaining optimal outcomes with low computational power. The findings highlight the importance of taking into account the computational efficiency while choosing a machine learning algorithm, especially when it comes to real-time implementation with limited resources. All quantitative training times and memory fingerprints used in the CES computation were strictly measured under the cloud infrastructure defined in Section 4.5.

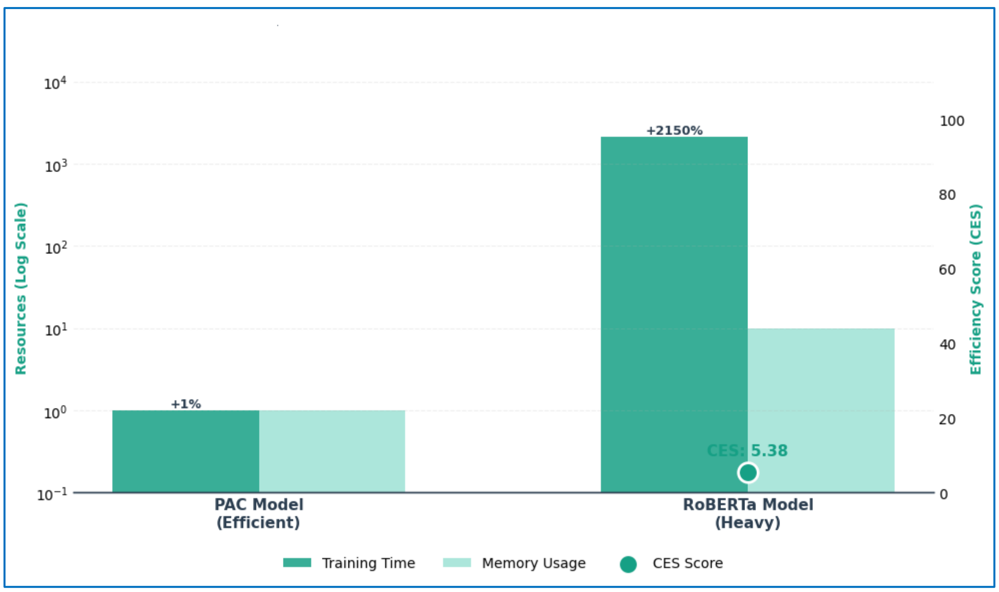

Figure 10: Comparative analysis of Compute Efficiency Score (CES) and resource consumption for PAC and RoBERTa models.

The conventional balance between cost and benefit of transformer networks can be seen from Figure 9. Even though the performance of RoBERTa is slightly better than PAC, this is done at the cost of significant computational efficiency. On the other hand, the PAC framework illustrates an efficient use of resources together with effective predictions. The data offer mathematical evidence showing that, with limitations, the cost associated with complex models is not efficient compared to the PAC framework.

6. Discussion

The empirical evidence that has been presented above offers a multivariate evaluation of the strengths and weaknesses of the PAC and RoBERTa methods in identifying misinformation. The current chapter summarizes this evidence with an aim to present the theoretical, statistical, and practical implications of this methodological experiment. With the Efficiency-Accuracy Dilemma considered in its wider context, this chapter challenges the established belief that more complex models are always superior, illustrating that assessments that factor in efficiency may lead to vastly differing paradigms.

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.2 june 2026

From the results above, it can be deduced that although the classifier model in use is linear, the Passive-Aggressive Classifier exhibits performance equal to that exhibited by the state-of-the-art RoBERTa transformer. The implication of such an equivalence in performance between the two models suggests that for fake news detection on a large scale, the TF-IDF vectorized form of words holds enough discriminatory information that allows for accurate fake news detection. Even though the current trend is towards transformer models, the results above suggest that conventional machine learning models exhibit high competitiveness in the context of fake news detection.

To confirm the statistical significance of the performance difference found, McNemar's test was conducted using the difference in classification of the two models. For this purpose, b represents the number of samples incorrectly classified by PAC and correctly classified by RoBERTa, while c represents the number of samples incorrectly classified by RoBERTa and correctly classified by PAC. Table 5 presents the contingency table constructed from the paired predictions.

Table 5: Contingency Table for McNemar's Test

	RoBERTa Correct	RoBERTa Incorrect
PAC Correct	—	c= 1
PAC Incorrect	b= 3	—

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ISSN (print): 2706- 6908, ISSN (online): 2706-6894

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The formula for McNemar test statistic is:

$$\chi^2 = (|b - c| - 1)^2 / (b + c) \qquad \text{… Equation 2}$$

For the values b = 3 and c = 1, the calculated value of p is 0.317. As p is greater than 0.05, the null hypothesis cannot be rejected, meaning that the difference in performance between PAC and RoBERTa is statistically insignificant. The above statistical result supports the conclusion drawn from the confusion matrix, where the number of misclassified samples was very few.

Conclusively, this analysis proves that the marginal improvement in accuracy of 0.06%, due to RoBERTa is not worth the computational resources involved. According to empirical findings, PAC (99.44%) provides functional equivalence to transformers in processing big datasets (44,898), and at the same time requires less computational resources and has lesser computation delays.

The paradox of efficiency vs accuracy discussed above poses a significant challenge to the currently dominant "Deep Learning First" philosophy. Our analysis revealed that both the approaches have limitations despite the complexity of the models. This is evident since the approaches are unable to accurately capture complex linguistic characteristics, especially where there is sarcasm and mixed deception. Therefore, considering an industrial setting, the PAC model appears to be the best choice.

University of Thi-Qar Journal

ISSN (print): 2706- 6908, ISSN (online): 2706-6894

Vol.21 No.2 june 2026

7. CONCLUSION

This paper provides an in-depth comparison between the classical methods and deep transformer models for fake news detection using the Passive Aggressive Classifier (PAC) and RoBERTa. While RoBERTa displays slightly superior accuracy levels, the non-significance test by McNemar reveals no statistical significance of their difference. On the other hand, the PAC reaches functionally equivalent results while having much less computational requirements and not causing memory saturation, thereby making it a promising approach suitable for streaming applications. This suggests that increasing the complexity of architecture does not necessarily lead to proportional increases in the predictive power of the model. However, there are certain limitations to be acknowledged. Firstly, the experiments involve the use of the English language only and, therefore, lack generalizability with regard to more morphologically rich languages such as Arabic. Secondly, bias within the sample collection process used in the experiment may undermine the results due to failure to detect the changing patterns of fraud. Thirdly, the assessment takes into account only formal news articles but not social media posts in which slang and abbreviations are commonly used. Fourthly, the experiments focus on unimodal textual data only. To address the aforementioned limitations, three promising avenues for future work are recommended. Firstly, XAI frameworks, such as SHAP and LIME, need to be incorporated into the model in order to achieve model transparency and explainable output. Secondly, the assessment metric needs to be expanded to include cross-lingual tests, in particular, taking into consideration the complexities of the Arabic language as well as the inclusion of additional contextual information. Thirdly, future work must investigate the development of ensemble models that combine the strengths of the PAC and RoBERTa.

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