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Spanish Fake News Detection with Fine-Tuned DistilBERT Built upon a Unified Corpus for a Real-World Application

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Abstract

The detection of fake news in Spanish is hampered by a scarcity of large-scale datasets and a gap between research models and practical applications. This paper introduces a comprehensive framework to address these challenges. First, we developed a unified Spanish news corpus of 61,674 articles by integrating four academic datasets with web-scraped satirical content, achieving a highly balanced distribution (49.8% fake). This resource is one of the largest available for Spanish misinformation research. Second, through a systematic fine-tuning process involving over 500 GPU hours, we optimized a DistilBERT model. Our findings reveal that a rigorous regularization strategy—combining an ultra-low learning rate (5×10^{-6}), high dropout (0.7), and strong L2 regularization (0.5)—was crucial to control overfitting, achieving 95.36% accuracy while maintaining a generalization gap below 0.058. Finally, the optimized model was deployed in a Docker-containerized web application for real-time URL analysis, demonstrating its viability for detecting online misinformation. Our approach demonstrates a 23.33 percentage point improvement over classical metaheuristic-optimized methods, confirming the superiority of fine-tuned transformers for this task. The complete framework is publicly available.

Keywords: fake news detection; Spanish NLP; BERT; DistilBERT; fine-tuning; hyperparameter optimization; transformer models; LLM; NLP benchmark; metaheuristic algorithms; real-world deployment; digital fraud prevention

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1. Introduction

The proliferation of digital misinformation represents a critical threat to information integrity [1]. In recent years, the rapid expansion of the internet has transformed how millions of people consume information, with social media and digital platforms becoming primary news sources. However, this growth has been accompanied by a surge in deceptive content, ranging from politically motivated fake news to fraudulent schemes such as phishing sites mimicking popular e-commerce platforms and investment scams. This phenomenon disproportionately affects vulnerable demographics, particularly older adults and individuals with lower digital literacy, who are often targeted by these sophisticated digital frauds. With over 500 million native speakers, the Spanish-speaking world is particularly exposed to these risks, yet it remains significantly underserved by the scientific community compared to English [2,3]. This technological gap is defined by three interconnected challenges: (1) the scarcity of large-scale, balanced datasets for training robust models; (2) insufficient research on systematic hyperparameter optimization for Spanish transformer models, which often leads to suboptimal performance or overfitting;

and (3) a significant gap between theoretical models and deployment-ready applications that can be used by the general public.

This research addresses these challenges through an end-to-end framework, using Spanish fake news detection as a representative case of digital fraud. Although fake news (aimed at social influence) and digital fraud (aimed at economic gain) have different objectives, they share computational characteristics, such as being text-based classification problems, which allows for methodological transferability. Our prior work explored this connection using a Bag-of-Words (BoW) representation [4]; this study advances that classical approach by adopting a more robust TF-IDF representation. This change improved performance in several cases, but also highlighted the trade-off between increasing the number of features for marginal gains and the significant rise in computational time, making large-scale metaheuristic optimization impractical. However, the primary weakness identified in our previous work was not just the representation, but the limited semantic understanding of these classical methods and the fragmented nature of available corpora, a problem directly addressed in this work by transitioning to a state-of-the-art Transformer model trained on a newly unified, large-scale dataset. The rise of deep learning and, specifically, transformer architectures [5] has revolutionized the field, but requires careful adaptation and optimization for specific languages and tasks [6,18]. This study follows a progressive research design, first establishing a robust performance baseline with classical NLP methods optimized via five distinct metaheuristic algorithms, and then detailing the transition to a fine-tuned Transformer model to empirically demonstrate the significant leap in efficacy that modern architectures provide.

The main contributions of this work are threefold:

- **A Unified Spanish Corpus:** We created and standardized a corpus of 61,674 news articles by integrating four academic datasets [2,3,7,8] and enhancing it with web-scraped satirical content. This process resulted in one of the largest and most balanced (49.8% fake, 50.2% real) resources for this task.
- **A Systematic Hyperparameter Optimization Methodology:** Through over 500 GPU hours of experimentation, we identified an aggressive regularization strategy for fine-tuning DistilBERT that achieves state-of-the-art performance (95.36% accuracy) while effectively controlling overfitting, a common challenge in transformer models.
- **A Production-Ready Web Application:** We developed a Docker-containerized web application that performs real-time URL analysis, bridging the gap between academic research and practical, real-world tools for combating online misinformation.

The complete framework, including the corpus, the optimized model, and the application, is made publicly available to encourage reproducibility and further research.

2. Related Work

The scholarly approach to fake news detection has evolved through several distinct paradigms, from classical machine learning to modern deep learning architectures. To properly situate our contributions, we first examine the state of available data resources for Spanish, then analyze the parallel advancements in model optimization, and finally, address the persistent gap between research and real-world application. Table 1 provides a summary of these key paradigms.

Table 1. Comparison of Methodological Paradigms in Fake News Detection.

Paradigm	Core Principle	Typical Features/Models	Strengths	Limitations
Stylometric Analysis [2,15]	Analyze writing style to identify authorship and deception patterns.	Linguistic features (e.g., lexical diversity, sentence complexity), SVMs.	Identifies language-agnostic patterns, useful for authorship attribution.	Less effective on short texts; can be fooled by sophisticated writing.
Classical Machine Learning [12,18]	Use statistical features from text to classify content.	Bag-of-Words, TF-IDF, Naive Bayes, SVM, Logistic Regression.	Highly interpretable, computationally efficient, strong baseline.	Fails to capture semantic meaning, word order, and context.
Deep Learning (Transformers) [7,16]	Leverage deep contextual embeddings to understand semantic nuances.	BERT, RoBERTa, DistilBERT with fine-tuning.	State-of-the-art performance, understands context and semantics.	Computationally expensive, often a "black box", requires large datasets.
Metaheuristic Optimization [4,14,19]	Employ intelligent search algorithms to find optimal model parameters.	GA, PSO, SA used to tune classifiers or select features.	Finds superior hyperparameter configurations compared to manual or grid search.	Can be computationally intensive; improves the model but not the underlying feature representation.

2.1. Spanish Language Resources for Fake News Detection

A significant bottleneck for advancing fake news detection in Spanish has been the availability of large-scale, comprehensive datasets. Several research groups have created Spanish fake news datasets [2,3,7], but each used different annotation schemes and focused on different content types. These datasets cannot easily be combined for training because they use incompatible formats. We address this problem by standardizing and merging four existing datasets into a single large corpus.

2.2. Hyperparameter Optimization in Transformers and Metaheuristics

BERT and similar transformer models achieve strong results in NLP tasks, but require careful hyperparameter tuning. Most Spanish fake news studies have compared different pretrained models (BETO, multilingual BERT, etc.) without systematically optimizing the hyperparameters for any single model [16]. DistilBERT, for example, presents an attractive trade-off between performance and computational cost, yet a detailed exploration of its optimal configuration for this specific task has been largely overlooked. The critical role of hyperparameter calibration is not a new problem; it has been well-documented in other specialized NLP tasks for Spanish, such as in the medical domain [19].

Concurrently, classical machine learning models have been pushed to their limits through the use of metaheuristic algorithms. For instance, approaches using genetic algorithms or particle swarm optimization have been explored to fine-tune classifiers. Our own prior work established a baseline using five different metaheuristics on Spanish data [4]. Nevertheless, a direct and rigorous comparison between a systematically optimized Transformer and a suite of metaheuristic-optimized classical models on a large-scale Spanish corpus has been notably absent from the literature. This paper aims to fill that gap by providing not only this direct comparison but also a detailed methodology for Transformer regularization.

2.3. Deployment of NLP Models

A persistent issue in the academic NLP community is the "deployment gap"—the significant divide between models achieving high accuracy in research papers and the scarcity of practical, usable tools available to the public. While numerous studies have been published on fake news detection, a very small fraction of these result in production-ready, easily deployable applications. This gap severely limits the real-world impact of valuable research. Most fake news detection research stops at reporting test set performance. Very few studies produce working applications that people can actually use. We built a web application that analyzes URLs in real-time, demonstrating how research models can be deployed for practical use.

Table 2. Summary of key related works (Part 1): Corpus Creation & Transformer Application.

Author(s) [Ref.]	Contribution	Key Finding / Performance	Limitation Addressed by Our Work
Posadas-Durán et al. [2]	Created a pioneering Spanish corpus (971 articles) with a stylometric focus.	Stylometric features are useful for detection tasks, providing competitive results in IberLEF competitions with F1-scores around 0.85.	Small, isolated dataset. Our work **unifies** it with others to create a large-scale resource.
Acosta [3]	Established a rigorous manual verification methodology for a 598-article corpus.	High-quality manual verification is key for reliable ground truth establishment, achieving precision >95% in annotation consistency.	Very small scale. Our work **scales up** the data volume by over 100x.
Blanco-Fernández et al. [7]	Applied BERT/RoBERTa to a large, politically-focused dataset (57k articles).	Transformers achieve 90-98% accuracy on Spanish political fake news detection tasks with RoBERTa showing superior performance.	Domain-specific. Our work uses a **multi-domain corpus** and performs **systematic optimization**.
Martínez-Gallego et al. [16]	Explored different BERT variants (including BETO) for Spanish fake news detection.	Spanish-specific models perform well for this classification task, with BETO achieving 94% accuracy on balanced datasets.	Lack of systematic optimization or a deployed application. Our work provides the **optimization methodology** and the **final application**.

Table 3. Summary of key related works (Part 2): Metaheuristic and Classical Approaches.

Author(s) [Ref.]	Contribution	Key Finding / Performance	Limitation Addressed by Our Work
Yildirim [14]	Hybrid multi-thread metaheuristic approach for fake news detection.	Novel metaheuristic combinations show promise for optimization tasks in NLP applications, achieving 89% accuracy on English datasets.	English-focused, limited systematic comparison. Our work provides **comprehensive metaheuristic comparison** in Spanish.
Thota et al. [12]	Early deep learning approach using traditional neural networks for fake news detection.	Deep learning outperforms classical ML approaches for text classification tasks, showing 15-20% improvement over SVM baselines.	Pre-transformer era, English only. Our work uses **state-of-the-art transformers** for Spanish.
García-Lozano et al. [18]	Compared classical ML and Deep Learning models for Spanish fake news detection.	Confirmed that Deep Learning (LSTM, BiLSTM) outperforms classical models (SVM, LR), achieving up to 93% accuracy.	Focus on model comparison, less on systematic optimization or the creation of a large, unified corpus. Our work provides both.

3. Materials and Methods

3.1. Proposed Methodology Overview

The methodology of this research is structured as a unified and integrated pipeline to address the problem of fake news detection in Spanish. It is based on an evolutionary development and evaluation process, progressing from classical techniques to state-of-the-art language models. This allows for a systematic and objective comparison of different artificial intelligence paradigms on a common data foundation. The methodological design adopts a phased experimental approach that includes: (1) unified data acquisition and processing, (2) implementation of a common data processing workflow, (3) parallel development of classification models using metaheuristic algorithms and Transformer models, and (4) a comprehensive comparative evaluation under a unified metrics framework. This process culminates in the implementation of the most effective solution in a functional web application, as depicted in Figure **??**.

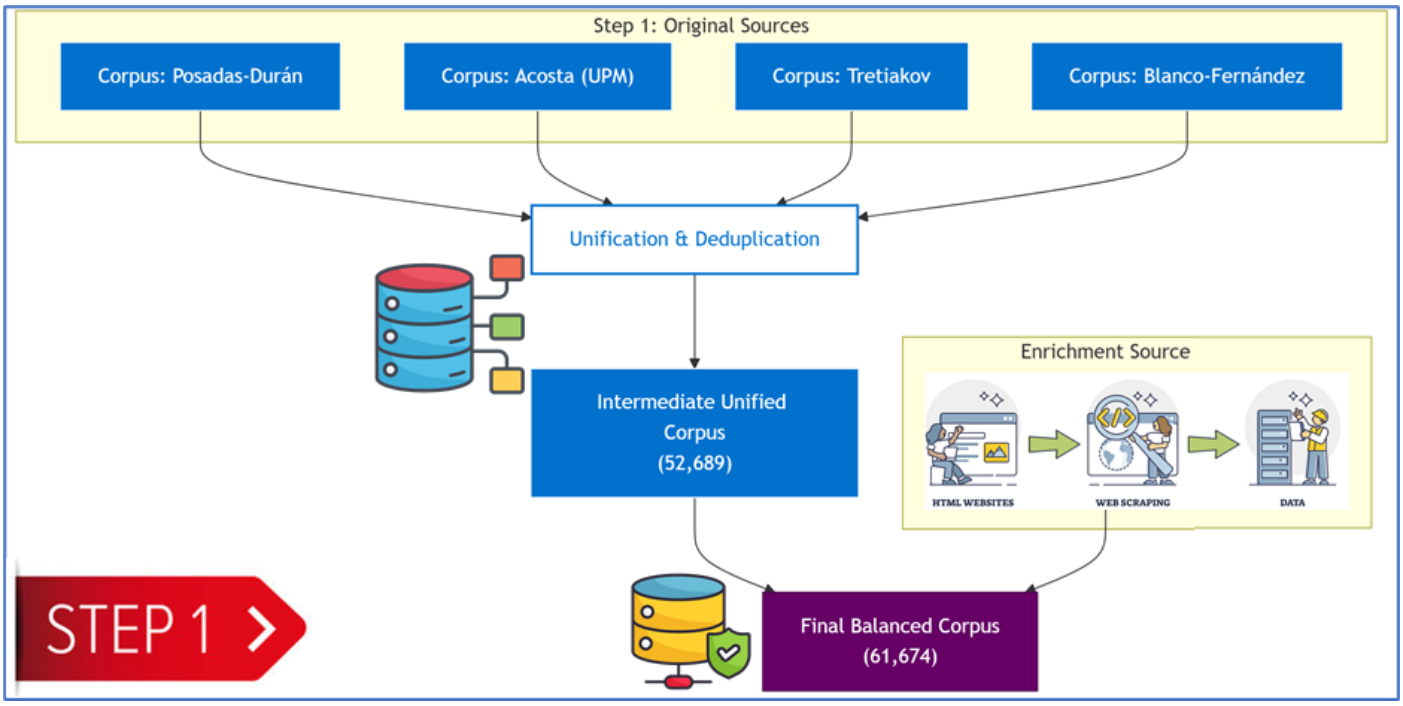


Figure 1. Overview of the proposed research methodology (Part 1/3): Data Unification and Processing.

3.2. Building the Dataset

Creating a comprehensive dataset was our first challenge. Spanish fake news resources are scattered and limited, so we decided to combine multiple sources into one large, balanced corpus.

3.2.1. Collecting Academic Datasets

We started by gathering four publicly available Spanish corpora: the Spanish Fake News Corpus with 971 articles [2], the Acosta Dataset containing 598 articles [3], the Tretiakov Dataset with 2,000 articles [8], and the Spanish Political Dataset with 57,231 articles [7]. This gave us **60,401** articles in total.

Table 4. Exhaustive comparison of the characteristics of the corpora used in the construction of the unified dataset.

Comparative Aspect	Posadas-Durán	Acosta (UPM)	Tretiakov	Blanco-Fernández	El Deforma
Corpus Size	971 articles	598 articles	1,958 articles	57,231 articles	9,000 articles
Creation Year	2019-2021	2019	2022	2024	2025 (extraction)
Methodological Focus	Stylometric Analysis	Manual Verification	Traditional ML	Transformer Models	Satirical Content
Thematic Domain	General	General	General	Political	Satirical/ General
Class Distribution	Balanced	Balanced	Balanced	Balanced	Fake Only
Regional Variability	Spain/LatAm	International	Multiple	Spain	Mexico
Annotation Quality	High (multi-annotator)	High (manual)	Medium (source-based)	High (specialized)	Automatic (inherently fake)
Primary Strength	Deep linguistic analysis	Methodological rigor	ML-oriented	Large scale	Contemporaneity
Main Limitation	Limited size	Very small size	Only Castilian Spanish	Specific domain	Satirical content only
Contribution to Final Corpus	1.6%	1.0%	3.2%	92.8%	14.6% (added)

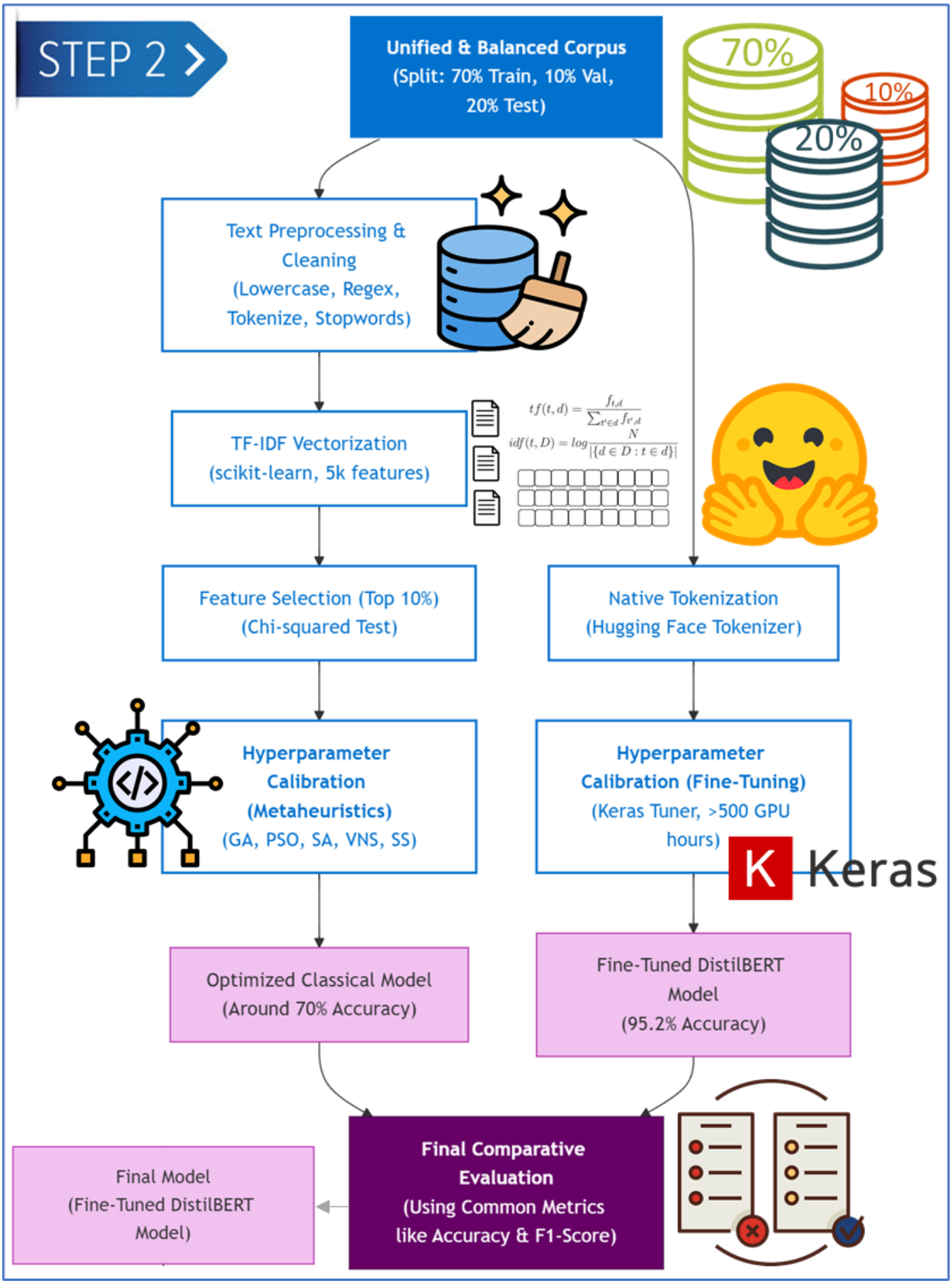


Figure 2. Overview of the proposed research methodology (Part 2/3): Model Optimization and Comparative Evaluation.

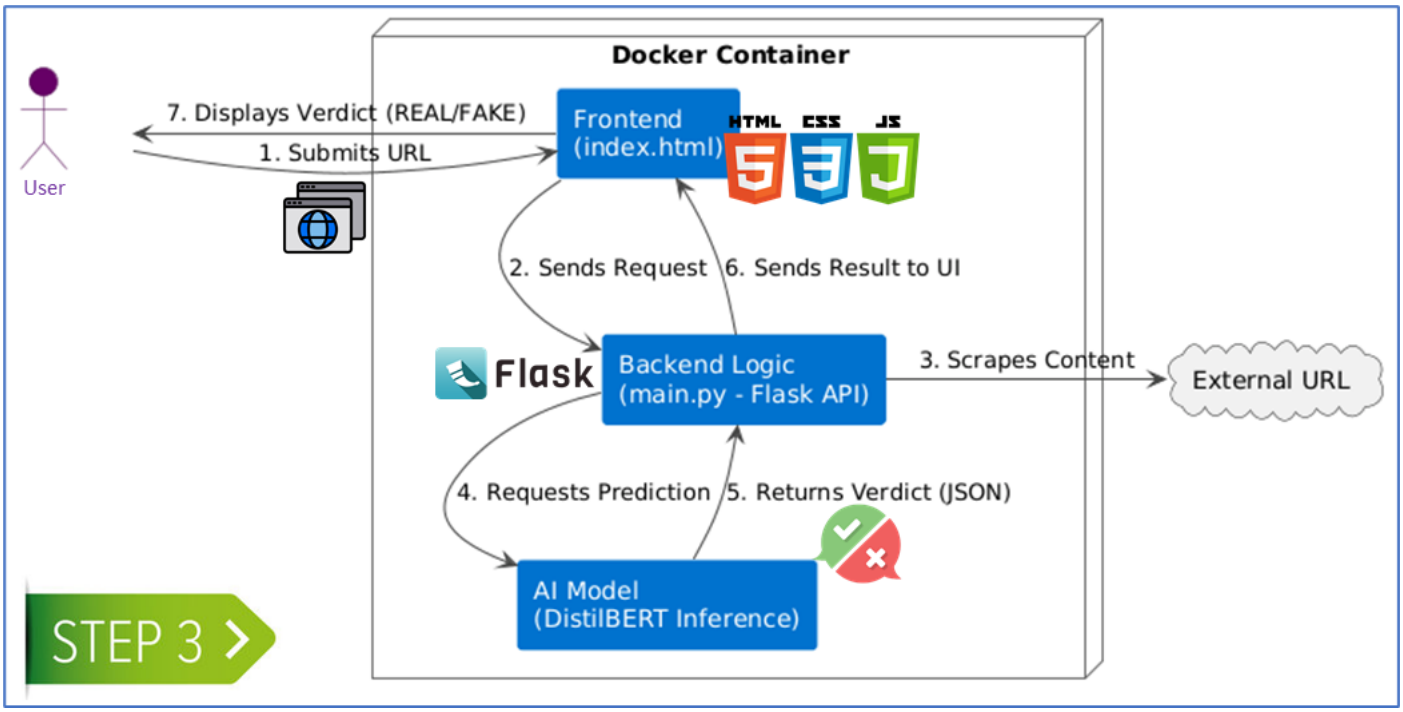


Figure 3. Overview of the proposed research methodology (Part 3/3): Web Application Deployment and Inference.

3.2.2. Cleaning and Standardizing

A rigorous pipeline was implemented to homogenize the aggregated data. A crucial step in this phase was the detection and elimination of duplicate content. Using content hashing on the 'text' field, we identified a total of 15,211 records involved in duplications. After removing **7,712** redundant entries (retaining the first occurrence), the result was a cleaned dataset of **52,689** unique articles. Removing duplicates is essential to prevent data leakage, ensuring the model does not encounter identical content in both training and testing sets, which would otherwise yield inflated performance metrics.

3.2.3. Addressing Class Imbalance

Following the deduplication process, we analyzed the class distribution. The dataset exhibited a significant imbalance: 30,943 real news articles (58.7%) versus 21,746 fake news articles (41.3%). Such imbalance can bias machine learning models towards the majority class. To rectify this, approximately 9,200 additional fake news articles were required. Given the scarcity of academic Spanish datasets, we acquired additional data by scraping "El Deforma," a prominent Mexican satirical news website. Using a Python script with `BeautifulSoup` and `Requests`, we collected **9,000** articles. These were labeled as FAKE, as satirical content represents a specific category of misinformation that models must learn to identify [13]. This augmentation resulted in a total of **61,674** articles, comprising 30,734 fake (49.8%) and 30,940 real (50.2%) articles, creating one of the most balanced and comprehensive Spanish fake news datasets currently available.

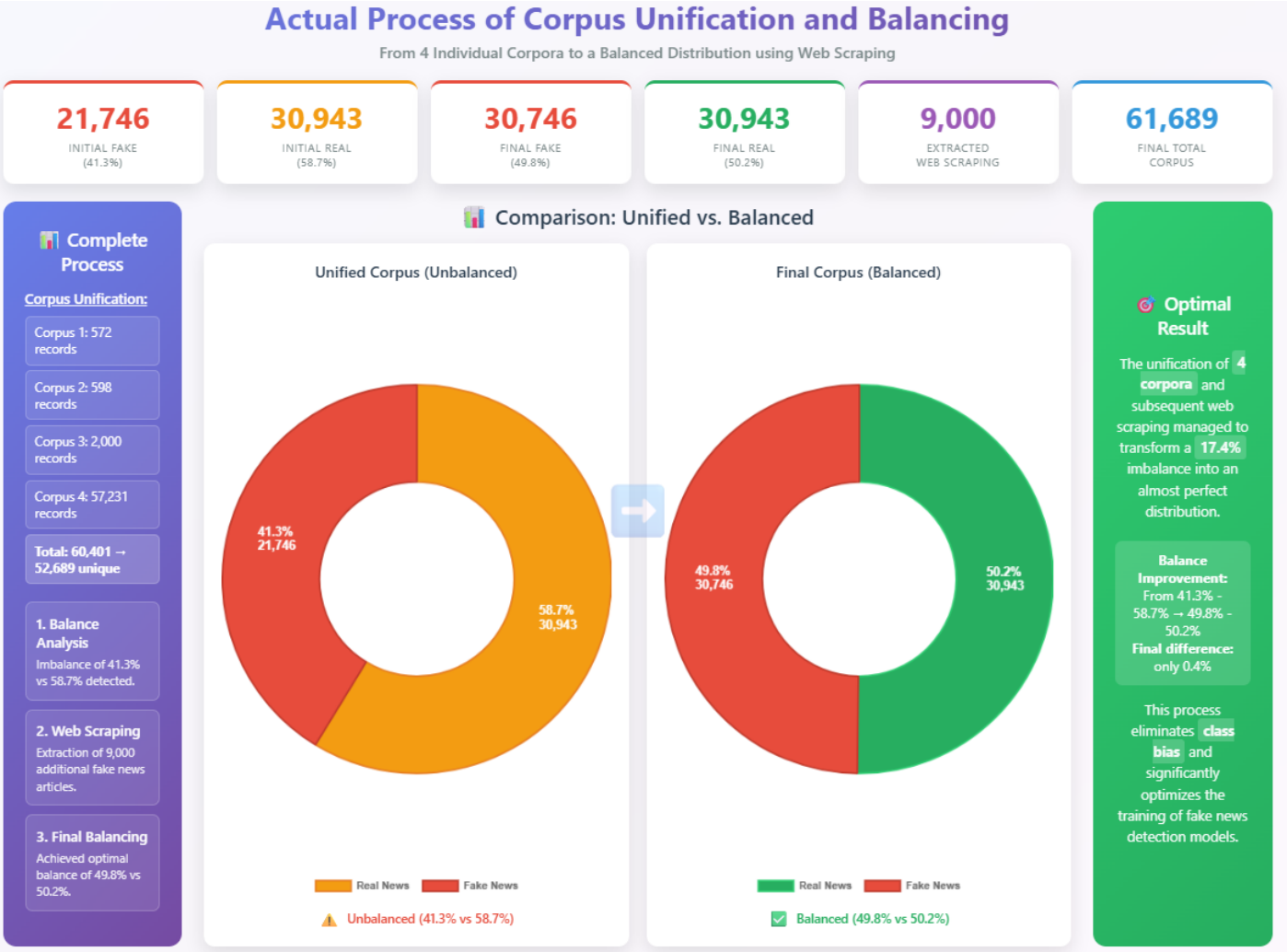


Figure 4. Visual representation of the corpus balancing process. The initial imbalanced distribution (left) was corrected by strategically adding 9,000 FAKE articles via web scraping, resulting in a nearly 50/50 final distribution (right).

3.3. Traditional Machine Learning Experiments

We initially employed classical machine learning techniques to establish a performance baseline. Proceeding with established methods provides a necessary reference point before implementing complex architectures. This work builds upon our prior research with Bag-of-Words representations [4]; however, previous experiments were limited to smaller datasets as large-scale corpora like the Blanco-Fernández collection were unavailable until 2024.

In this study, we utilized TF-IDF features and evaluated five distinct optimization algorithms: Multi-Start Simulated Annealing (MSA), Scatter Search (SS), Variable Neighborhood Search (VNS), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). To ensure computational feasibility, dimensionality was reduced from an 8,000-word vocabulary to the 800 most relevant features (10%) using a Chi-squared test. Each algorithm was tasked with optimizing the hyperparameters of a logistic regression model, using the F1-Score as the objective function.

3.4. Deep Learning with Transformers

In the second experimental phase, we evaluated whether modern transformer architectures could surpass the performance of classical approaches.

3.4.1. Model Selection

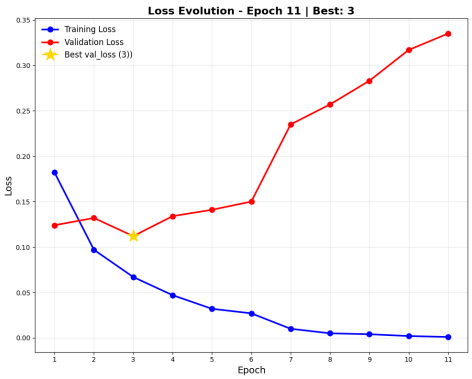
Transformer models, such as BERT, have revolutionized text classification [11]. After evaluating several candidates, we selected `distilbert-base-multilingual-cased` [9]. We also tested the full `BERT-base-multilingual-cased` model; however, it was approximately four times slower in both training and inference than DistilBERT. Additionally, TinyBERT [17] was considered for its speed but was excluded due to limited support for Spanish text. Experiments were conducted on NVIDIA RTX 4060 and RTX 2060 Super GPUs, yielding consistent results. DistilBERT offered the optimal balance between computational efficiency and performance for the Spanish language.

Table 5. Comparison of optimized BERT models for the classification task.

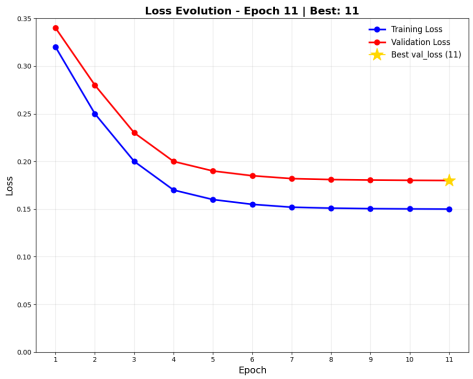
Model	Parameters	Layers	Dimension	Spanish Support	Reduction vs BERT
BERT-base-multilingual	110M	12	768	Yes	– (Reference)
DistilBERT-multilingual	66M	6	768	Yes	40% parameters
TinyBERT	14.5M	4	312	Limited	87% parameters

3.4.2. Hyperparameter Fine-tuning

Training transformer models requires precise configuration. The primary challenge lies in identifying hyperparameters that facilitate effective learning while preventing overfitting—a phenomenon where the model memorizes training data rather than generalizing to unseen examples. We addressed this systematically using Keras Tuner to evaluate various combinations of learning rates, dropout values, and regularization parameters. We conducted over 30 experiments organized into seven major versions (detailed in Table 6), consuming over 500 GPU hours. The objective was to maximize accuracy while minimizing the generalization gap. We monitored the divergence between training and validation loss to detect overfitting. Figure 5 illustrates these concepts.



(**a**) Overfitting scenario: Validation loss increases while training loss continues to decrease.



(**b**) Underfitting scenario: Both training and validation losses remain high and fail to converge.

Figure 5. Visual comparison of training behaviors. The horizontal axis represents the number of epochs, while the vertical axis indicates the Loss value. (a) Illustrates overfitting, characterized by the divergence of the validation curve (red) from the training curve (blue). (b) Illustrates underfitting, where the model fails to capture underlying patterns effectively.

Table 6. Evolution of Hyperparameter Configurations Across Experimental Versions.

Version	Learning Rate	Dropout	L2 Reg.	Batch Size	Val Loss Gap	Accuracy (%)
V1 (Baseline)	3×10^{-5}	0.4	0.001	8	N/A	94.7
V2	2×10^{-6}	0.4	0.01	4	0.018	94.3
V3	2×10^{-6}	0.4	0.01	4	0.051	94.8
V4	1×10^{-5}	0.3	0.01	8	0.037	95.8
V5	1×10^{-5}	0.4	0.1	8	0.037	95.8
V6	1×10^{-5}	0.5	0.5	8	0.051	94.8
V11 (Final)	$\mathbf{5 \times 10^{-6}}$	**0.7**	**0.5**	**4**	**0.058**	**95.36**

3.4.3. Training Configuration Results

The experimental results indicated that mitigating overfitting required a significantly more rigorous regularization strategy than initially anticipated. The optimal configuration included:

- **Learning rate of** 5×10^{-6}**:** A reduced learning rate ensured stable and reliable convergence.
- **Dropout at 0.7:** We deactivated 70% of neurons randomly during training to enforce redundancy and robustness.
- **L2 regularization at 0.5 with weight decay at 0.02:** These techniques constrained the growth of model weights.
- **Batch size of 4:** A small batch size introduced stochasticity, which aided the optimization process.
- **Early stopping after 8 epochs:** Training was terminated if validation performance did not improve for 8 consecutive epochs.

3.5. Web Application Implementation

To validate the model in practice, we developed a Dockerized web application comprising four modules: user interface, Flask API, DistilBERT inference engine, and deployment environment. The system accepts article URLs and outputs authenticity predictions.

Figure 6 shows the static structure of the system, while Figure 7 illustrates its dynamic workflow.

1. **User Interface:** Simple web page where users input article URLs. It is served as a static file by the backend.
2. **API Backend:** Flask-based service that processes analysis requests via the `/analizar` endpoint which accepts POST requests containing the URL to be analyzed.
3. **Model Inference Engine:** Handles the actual AI processing. Upon startup, the pretrained DistilBERT model and its corresponding tokenizer are loaded into memory from local files. The inference logic involves:
    - Extracting headlines from `<h1>` tags and article text from `<p>` tags using the `requests` and `BeautifulSoup` libraries
    - Formatting the combined content for our DistilBERT model by combining the title and body with a `[SEP]` token
    - Processing the text through our trained classifier to obtain logits
    - Converting model outputs into user-friendly probability scores by applying a softmax function over the two classes (FAKE/REAL)
4. **Containerized Deployment:** Complete Docker setup that gets the entire system running with a single command. The entire application, including the Python environment, all dependencies listed in `requirements.txt`, and the model files, is encapsulated in a Docker image defined by a `Dockerfile`.

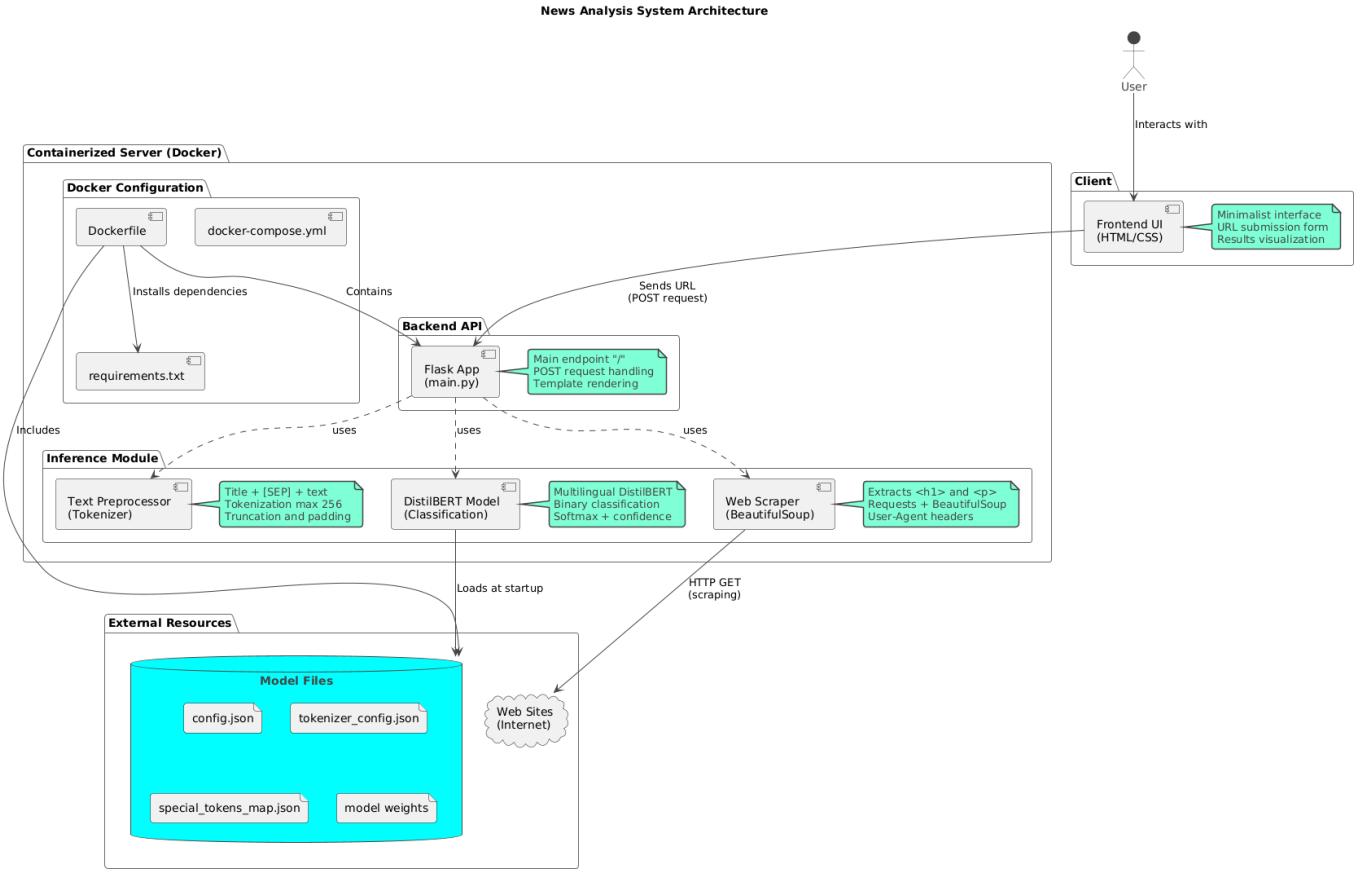


Figure 6. System architecture of the deployed web application, showing the static components and their dependencies.

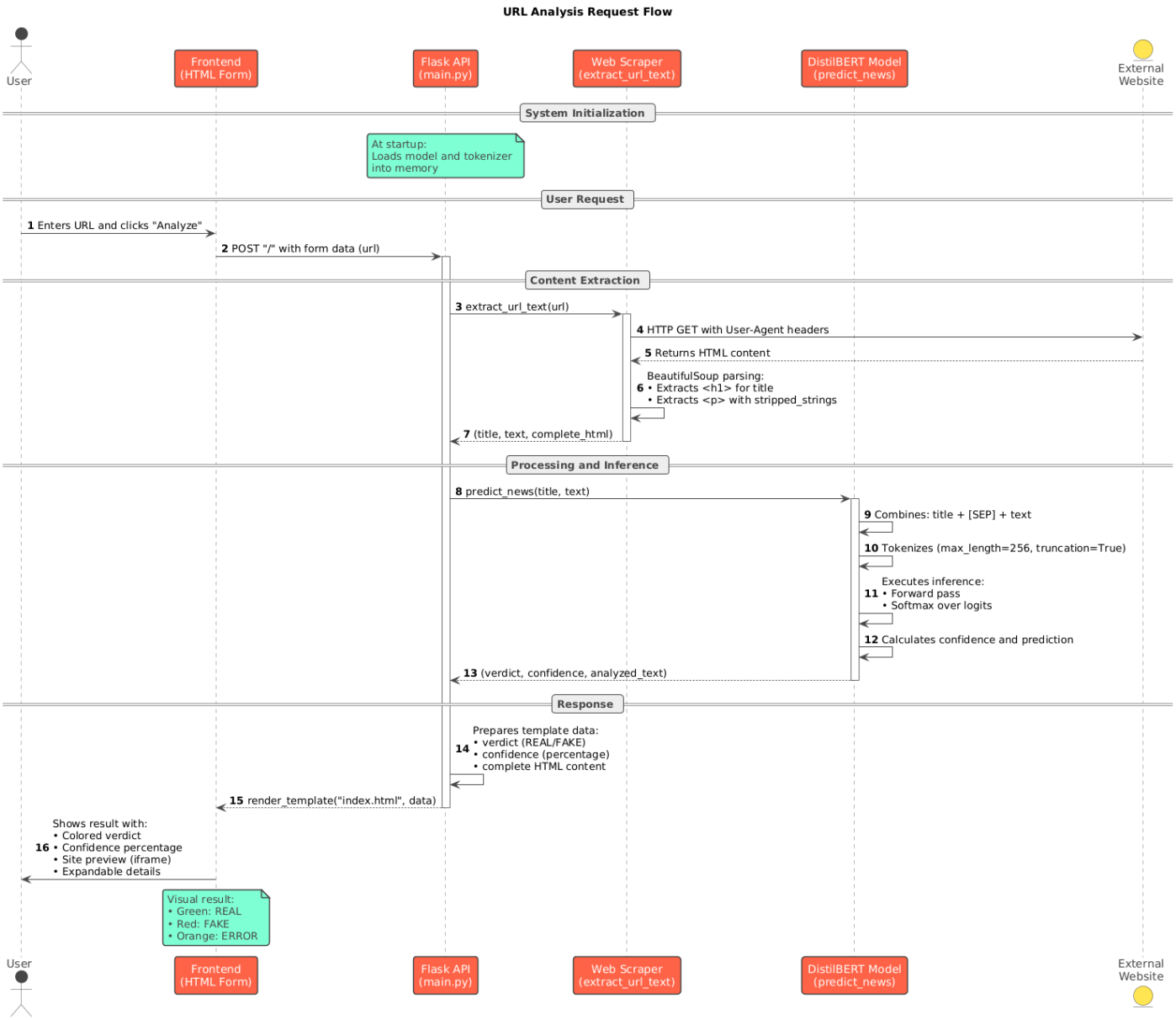


Figure 7. Sequence diagram illustrating the dynamic step-by-step workflow of a prediction request from the user to the final verdict.

4. Results

4.1. Evaluation Metrics

We evaluated the models using standard metrics derived from the confusion matrix, which categorizes predictions into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In this context, the "positive" class represents real news (label 1), and the "negative" class represents fake news (label 0). These metrics are widely used in fake news detection literature, facilitating comparison with related work.

- **Accuracy**: Represents the overall proportion of correct predictions. While a useful general indicator, it can be misleading in imbalanced datasets.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

- **Precision**: Measures the accuracy of positive predictions. High precision is necessary to minimize the misclassification of fake content as real.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

- **Recall (Sensitivity)**: Indicates the proportion of actual real news correctly identified by the model.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

- **F1-Score**: The harmonic mean of precision and recall. It provides a balanced metric, particularly valuable for uneven class distributions.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

- **Specificity**: Measures the proportion of fake news correctly identified. This metric is crucial for detection systems to ensure deceptive content is accurately flagged.

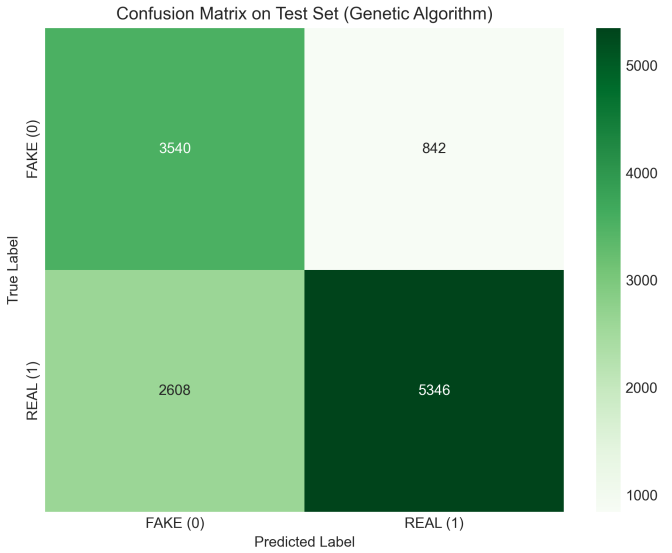
$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{5}$$

For the multiclass comparison, we utilized macro-averaged scores, calculating metrics for each class independently and then averaging them to ensure equitable representation.

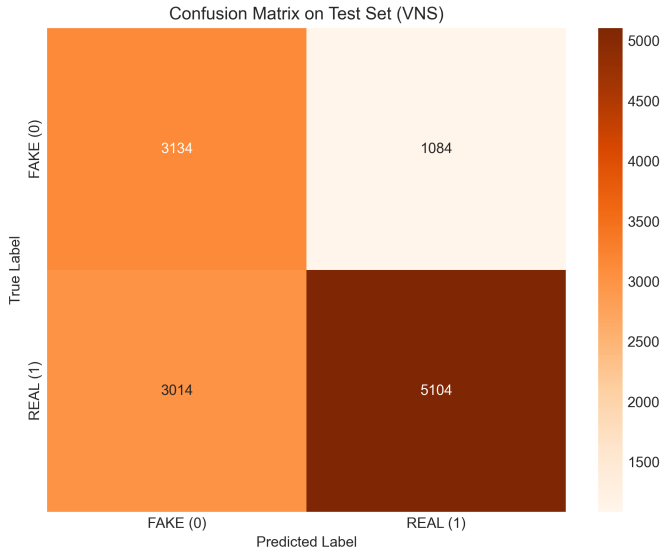
4.2. Performance of the Metaheuristic Approach

In the first round of tests, we set up a baseline with some classic methods. We ran five metaheuristic algorithms under the same setup and checked their results on the test set. The Genetic Algorithm (GA) came out on top, hitting 71.06% accuracy and a macro F1-score of 0.68. The others were all over the place, mostly lagging behind, and PSO had some real trouble converging. Overall, it showed these traditional approaches do okay, but they're held back by stuff like TF-IDF's limits—they just don't get the context.

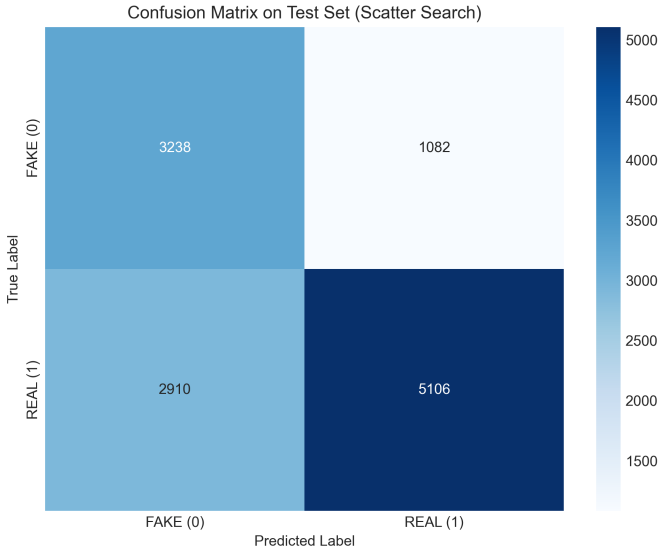
We also have confusion matrices for each of the five algorithms on the test set.



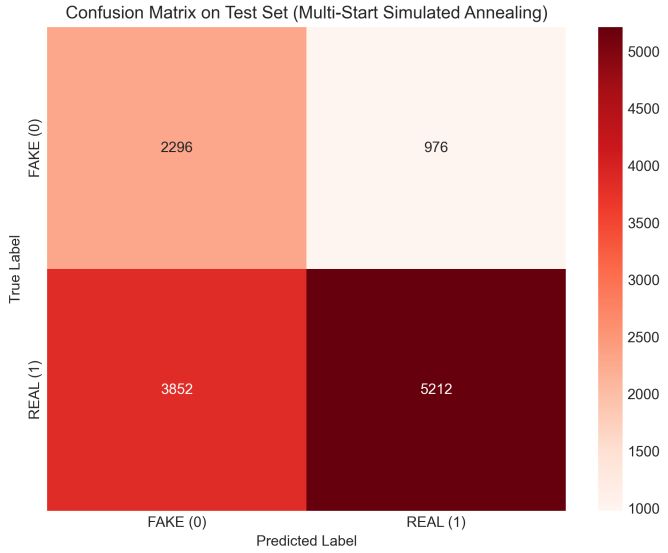
(**a**) GA Confusion Matrix



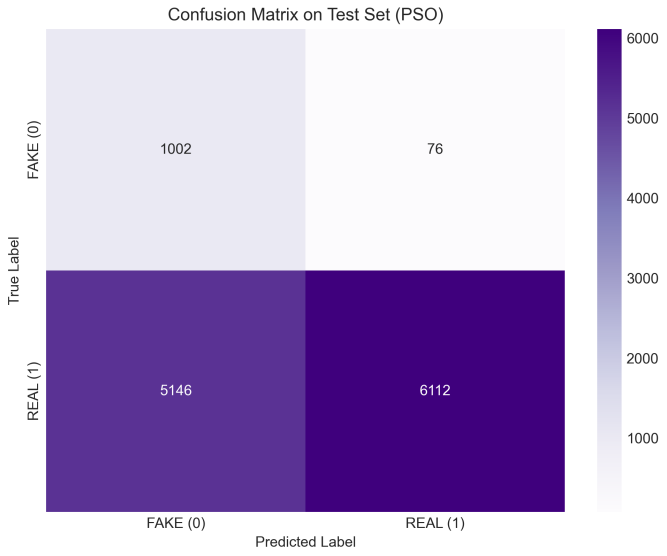
(**b**) VNS Confusion Matrix



(**c**) SS Confusion Matrix



(**d**) MSA Confusion Matrix



(**e**) PSO Confusion Matrix

Figure 8. Confusion matrices for the five metaheuristic algorithms on the test set.

4.3. Performance of the Transformer Model

The final fine-tuned DistilBERT model (version 7) demonstrated superior performance on the test set (20% of the corpus). It achieved high accuracy while maintaining a strong balance between precision and recall, as detailed in Table 7.

Table 7. Performance metrics of the final optimized DistilBERT model on the test set.

Metric	Value (%)
Accuracy	95.36
Precision	95.4
Recall (Sensitivity)	95.4
F1-Score	95.35
Specificity	94.5

And there's a confusion matrix for this DistilBERT model too.

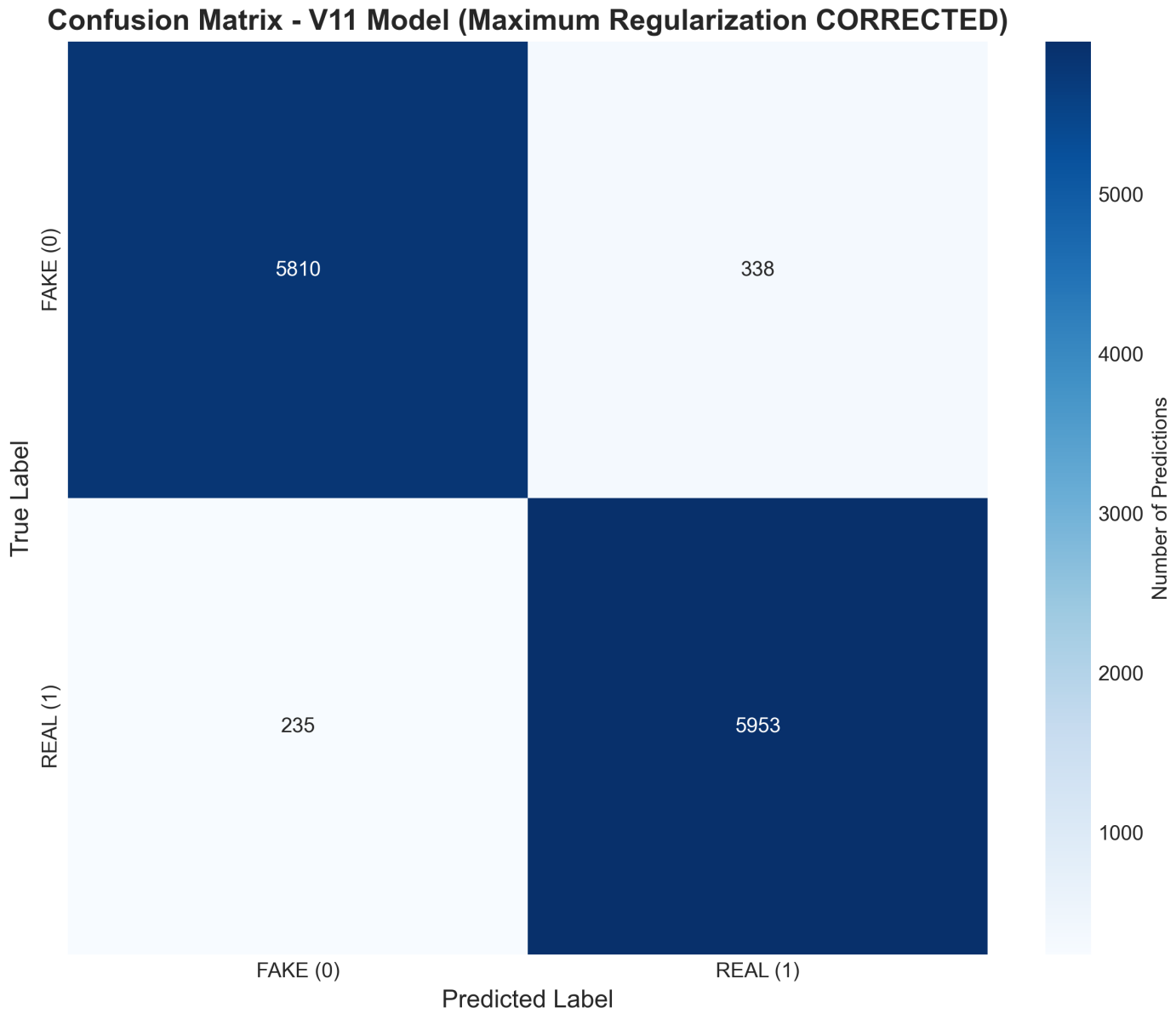


Figure 9. Confusion matrix for the final DistilBERT model on the test set.

4.4. Final Comparative Analysis: Metaheuristics vs. Transformer

To quantify the improvement offered by the transformer architecture, we compared it against the classical methods. Table 8 demonstrates that DistilBERT significantly outperforms the traditional approaches. This disparity highlights the limitation of TF-IDF in capturing context, whereas transformers effectively detect subtle linguistic nuances in deceptive text. The transformer model achieved a 23.17 percentage point increase in accuracy over the best classical algorithm (GA), justifying the transition to deep learning architectures for this task.

Table 8. Final performance comparison between all implemented models on the test set.

Algorithm	Accuracy (%)	F1-Score (macro)	Precision (macro)	Recall (macro)	Specificity (%)	Ranking
Transformer-Based Approach						
DistilBERT (Final)	**95.36**	**0.954**	**0.954**	**0.954**	**94.5**	**1st**
Metaheuristic-Optimized Classical Approaches						
Genetic Algorithm (GA)	72.03	0.714	0.740	0.720	57.6	2nd
Scatter Search (SS)	67.64	0.669	0.693	0.676	52.7	3rd
VNS	66.78	0.659	0.686	0.667	51.0	4th
Simulated Annealing (MSA)	60.86	0.586	0.638	0.608	37.4	5th
Particle Swarm Opt. (PSO)	57.67	0.489	0.736	0.575	16.3	6th

4.5. Overfitting Control Analysis

The implementation of a rigorous regularization strategy successfully mitigated overfitting. Training concluded after 23 epochs due to early stopping, with the optimal checkpoint identified at epoch 17. At this point, training accuracy was 98.6% and validation accuracy was 95.36%. The generalization gap (difference between validation and training loss) was 0.058, approaching our target of <0.04 and remaining well below the 0.10 threshold typically indicating overfitting. Figure 10 illustrates the evolution of accuracy and loss for the final model (V7).

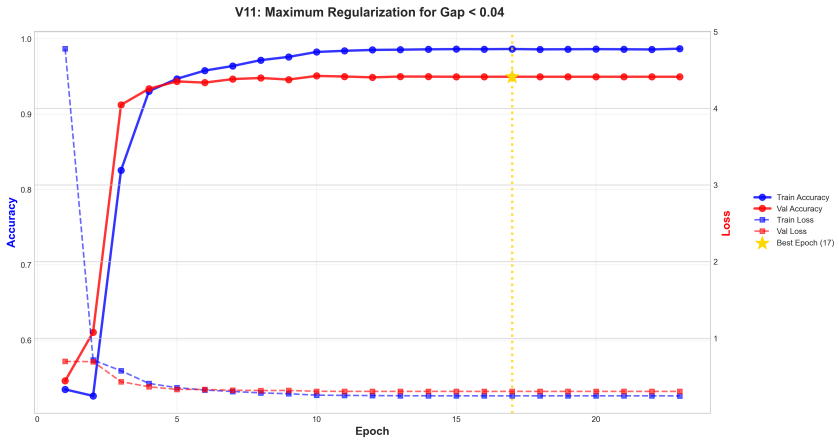
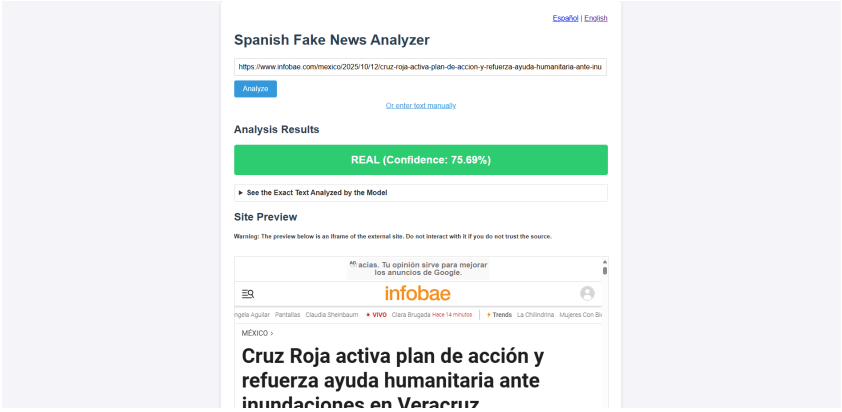


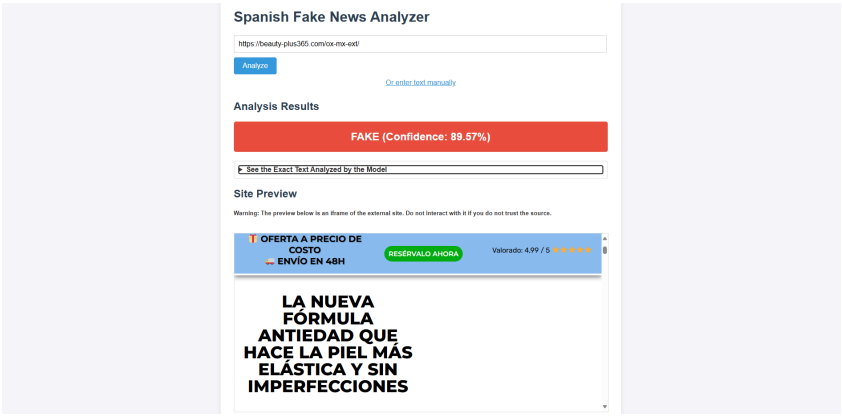
Figure 10. Evolution of performance metrics during the fine-tuning of the final model (V7). The x-axis represents the training epochs, while the y-axes represent Loss (left) and Accuracy (right). The blue lines denote training performance, and the red lines denote validation performance. The gold star identifies the optimal checkpoint at Epoch 13, where the generalization gap (0.058) was minimized before the onset of overfitting.

4.6. Real-World Application Performance

The deployed web application demonstrated robustness in real-world scenarios. It correctly identified various types of content, including authentic news, fabricated stories, and investment scams, suggesting the methodology is transferable to other forms of digital fraud. Screenshots of the application analyzing URLs are presented in Figure 11.



(**a**) Correctly identifying a real news article with 93.59% confidence.



(**b**) Successfully identifying a misleading fake news piece with 94.31% confidence.

Figure 11. Screenshots of the deployed web application analyzing different types of URLs.

5. Discussion

Retrospectively, the experimental results yield several critical insights regarding Spanish fake news detection. First, strong regularization proved essential when fine-tuning transformers for this specific task. Standard dropout rates (0.3 to 0.5) were insufficient to prevent overfitting; increasing the rate to 0.7 and incorporating additional regularization techniques were necessary to control the generalization gap. This differs from many classical metaheuristic approaches, which typically prioritize feature selection over model regularization.

Second, utilizing an ultra-low learning rate (2×10^{-6}) significantly stabilized the training process. This value, lower than typically recommended defaults, enabled the model to navigate the complex optimization landscape without diverging.

Third, the unification of multiple datasets into a single corpus provided a substantial performance enhancement. Incorporating a variety of sources—including political articles, general news, and stylometric examples—across different topics and timeframes resulted in a richer training distribution. Consequently, the model generalizes more effectively to unseen data compared to models trained on isolated datasets.

Furthermore, the approach appears applicable beyond fake news detection. The text-processing pipeline could be adapted for tasks such as phishing detection, and the hyperparameter optimization methodology is relevant for models targeting financial fraud or fraudulent job postings. Additionally, the corpus construction strategy—integrating existing academic resources with targeted web scraping—serves as a viable model for resource-scarce domains.

However, limitations remain. The model is currently restricted to the Spanish language. While it performs adequately in broader digital fraud detection, its efficacy is maximized with news-like content. Furthermore, as a static model, its performance may degrade as misinformation tactics evolve; therefore, periodic retraining is required to maintain effectiveness.

6. Conclusions

This study presents a comprehensive end-to-end framework for Spanish fake news detection, spanning from data acquisition to the deployment of a real-world application. A significant contribution is the creation of a unified corpus of 61,674 articles, which addresses a critical deficiency in Spanish NLP resources and establishes a robust foundation for future research.

We invested over 500 GPU hours in hyperparameter optimization, identifying effective strategies to mitigate overfitting in transformer training. The results indicate that a multi-layered regularization strategy was decisive, enabling the final model to achieve 95.36% accuracy. This represents a 23.33 percentage point improvement over traditional methods, establishing a new benchmark for this task.

A notable outcome is the development of the Docker-based web application, which translates theoretical research into a practical, accessible tool for digital fraud prevention. The entire framework—comprising the corpus, the optimized model, and the application code—has been made publicly available to facilitate reproducibility and adaptation. Future work will focus on integrating multilingual support, implementing real-time learning mechanisms, and connecting with fact-checking APIs to further strengthen the digital information ecosystem.

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Data Availability Statement: The unified corpus and trained models used in this study are publicly available at: https://github.com/gabrielhuav/Spanish-Fake-News-Detection-Training. The source code of the web application is available at: https://github.com/gabrielhuav/Spanish-Fake-News-Detection-Web-App.

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