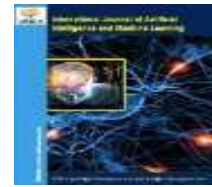




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An Interpretable Parameter Tuning Strategy for Machine Learning-Based Fake News Detection

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Abstract

Automation of fake news detection has become a significant research challenge due to the growing spread of false information through digital media. While machine learning models have shown encouraging results in the categorization of textual false news, their efficacy is heavily reliant on the choice of suitable parameters. Current research frequently uses parameter tuning methods directly without methodically examining the underlying performance constraints of baseline models, which could lead to ineffective parameter search space exploration. A methodology for parameter adjustment for machine learning-based fake news detection is proposed in this paper. The approach draws a connection between model shortcomings and pertinent parameter configurations by examining the behavior of four baseline classifiers: Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine. Following that, Random Search is used to quickly assess chosen parameter combinations and find appropriate configurations for every classifier. The experimental study shows that different machine learning models need different parameter choices in order to achieve effective generalization and consistent performance. By establishing tuned baseline models for further ensemble learning and enhancing our understanding of how parameter configurations affect model behavior, the suggested framework advances the field of fake news detection research. The study offers a comprehensible and computationally efficient basis for creating reliable machine learning-based false news identification systems.

Keywords- Fake news detection, machine learning, parameter tuning, Random Search parameters, text classification

1. Introduction

False news detection is a crucial topic for research in the fields of "natural language processing" and "machine learning," as the exponential growth of digital media platforms has continuously increased the spread of incorrect information. Classical machine learning models including "Logistic Regression," "Support Vector Machines," "Decision Trees," and "Random Forests" have been used extensively in the development of automated false news detection systems [1][2]. Together with feature extraction methods such as TF-IDF, these models have shown encouraging results in the classification of textual data [3]. However, choosing the right parameters—which regulate decision boundaries, learning behavior, and model complexity—is crucial to their efficacy [6]. Even while parameter adjustment is crucial, the majority of current research uses optimization methods like Grid Search or Random Search without first examining the intrinsic drawbacks of baseline models [5]. This frequently results in ineffective parameter space exploration and subpar model performance. Inadequate parameter selections can lead to under-fitting, over-fitting, and poor generalization in high-dimensional text classification problems like fake news detection [18]. Therefore, before using optimization approaches, a methodical methodology that diagnoses model performance is required. In order to close this gap, this study presents a pre-tuning parameter system that assesses baseline classifiers with default parameters and finds performance flaws. Under-fitting, over-fitting, and class imbalance are among the problems that the framework focuses on identifying and mapping to appropriate parameters. The suggested method offers an organized basis for effective and focused parameter optimization by clearly defining the relationship between model behavior and parameter values. This approach to parameter adjustment improves interpretability and reliability in false news detection systems in addition to model performance.

2. Related Work

Recent advancements in fake news detection have extensively explored the application of machine learning and deep learning techniques for text classification. Current literature in fake news detection focuses heavily on feature engineering and ensemble architectures. While papers cite the use of Randomized Search for optimization, there is a distinct lack of analyzation regarding the relationship.

Table 1: Literature review of existing studies

Authors	Year	Objective	Model	Parameters	Key Findings
R. Patel et al. [1]	2025	To optimize fake news detection using metaheuristic algorithms	Ensemble Models	Optimization parameters	Improved performance using optimized ensemble technique
M. K. Singh et al. [2]	2024	To detect fake news using transformer-based models	Transformer (BERT-like)	Learning rate, epochs	Achieved high accuracy with deep contextual learning
S. Sharma et al. [3]	2023	To enhance fake news detection using hybrid DL model	Hybrid DL Model	Learning rate, batch size	Improved classification accuracy using hybrid approach
D. Jurafsky & J. Martin [4]	2023	To provide NLP foundations	NLP Models	General Parameters	Established theoretical base for language processing
P. Probst et al. [5]	2019	To analyze importance of parameters	ML Models	General parameters	Highlighted impact of tuning on model performance
A. Géron [6]	2019	To implement ML models with tuning	ML Models	Multiple parameters	Practical guide for parameter tuning
C. Aggarwal [7]	2018	To study ML techniques for text	Text Classification Models	Default parameters	Explained challenges in high-dimensional text data
S. Raschka & V. Mirjalili [8]	2017	To implement ML algorithms	ML Models	Various parameters	Explained practical ML implementations
W. Y. Wang [9]	2017	To introduce fake news dataset (LIAR)	Benchmark Dataset	Default parameters	Provided dataset for evaluation
K. Shu et al. [10]	2017	To detect fake news using data mining	ML Models	Multiple parameters	Proposed content-based detection
H. Drucker et al. [11]	2017	To develop SVM regression	SVM	Kernel, gamma	Improved regression performance
I. Goodfellow et al. [12]	2016	To develop deep learning models	Deep Learning	Learning rate, epochs	Introduced DL fundamentals
Z. Zhang [13]	2016	To explain KNN algorithm	KNN	k-value	Basic ML classification explanation
T. Chen & C. Guestrin [14]	2016	To develop XGBoost algorithm	Boosting Model	Learning rate, depth	Improved performance with boosting
Y. LeCun et al. [15]	2015	To advance deep learning	Neural Networks	DL parameters	Highlighted importance of DL models
V. Vapnik [16]	2015	To explain statistical learning theory	SVM	Kernel, C	Provided theoretical ML foundation
N. Conroy et al. [17]	2015	To detect deception in news	ML Models	Multiple parameters	Early fake news detection methods
T. Mikolov et al. [18]	2013	To develop word embeddings	Word2Vec	Vector size	Improved text representation
G. James et al. [19]	2013	To introduce statistical learning	ML Models	General parameters	Provided ML fundamentals

J. Bergstra & Y. Bengio [20]	2012	To optimize parameters	ML Models	Search space	Random Search effective
F. Pedregosa et al. [21]	2011	To provide ML library (Scikit-learn)	ML Toolkit	All parameters	Enabled easy ML implementation
J. Friedman [22]	2010	To develop gradient boosting	Boosting	Learning rate	Improved prediction accuracy

Studies such as Shu et al. [10] provide comprehensive surveys highlighting the effectiveness of machine learning models in identifying misinformation using linguistic and social context features. Traditional approaches utilizing 'TF-IDF' representations combined with classifiers like "Logistic Regression" and "SVM" have shown competitive performance due to their simplicity and efficiency [3]. Furthermore, ensemble methods such as 'Random Forest' and 'boosting' techniques have been employed to enhance classification accuracy by combining multiple learners [4][21]. Parameter tuning has been recognized as a crucial step in improving model performance. Some of studies demonstrated that Random Search is more efficient than Grid Search for hyper-parameter optimization, especially in high-dimensional spaces[2]. Similarly, [5] emphasized the importance of selecting appropriate hyper-parameters to balance bias and variance in 'machine learning models'. In the context of "fake news detection", recent studies have incorporated optimization techniques such as 'Bayesian optimization' and 'meta-heuristic algorithms' to achieve better results [6][7][11].

The absence of pre-tuning analysis, however, is a significant drawback noted in the body of current literature. The majority of research concentrates on the correctness of the end model without looking into the root causes of subpar baseline model performance. Blind tuning, in which hyper-parameter optimization is carried out without comprehending model-specific flaws, results from a lack of systematic investigation [12]. The difficulties presented by high-dimensional sparse feature spaces produced by "TF-IDF," which greatly affect parameter behavior, have also received little attention [18]. In order to overcome these constraints, this work proposes a diagnostic-driven method that creates a mapping between hyper-parameters and performance gaps and assesses baseline models before adjusting. By improving optimization efficiency and deepening our understanding of model behavior, this method closes a major research gap in the literature on fake news identification.

3. Research Methodology

The research methodology for the study follows a design to move beyond traditional "blind" parameter selection by establishing a clear relationship between baseline model deficiencies and parameter configurations.

3.1 Pre-Tuning Technique

Pre-Tuning refers to all the structural, data-handling and baseline preparation steps performed before executing parameter selection such as Random Search or Grid Search. It ensures that the parameter search space is well-defined, the dataset is leak-free and model evaluation metrics are valid. Establishing a baseline for parameters guarantees that performance boosts after tuning would represent model optimization rather than dataset anomalies. By identifying vulnerabilities such as over-fitting and high dataset dependency, the process utilized a Random Search method to efficiently explore lots of parameter combinations. The pre-tuning procedure is a systematic step designed to identify best parameters for baseline models logistic regression, support vector machine, decision tree and random forest to prepare them for a stacking ensemble. Ultimately, this procedure reduced mitigated over-fitting, improved individual accuracy and created a stable foundation for the final fake news detection framework.

3.2 Baseline Models

The specified machine learning algorithms for this study were chosen because of their capability in managing high-dimensional text data and their efficiency.

Table 2: Comparative Characteristics, Architectural Roles and Limitations of Baseline Classifiers

Baseline Model	Core Strengths	Operational Role	Key Limitations
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Logistic Regression	Simple, highly interpretable, and computationally efficient for linearly separable datasets.	Serves well as a baseline classifier and is particularly useful as a meta-classifier in stacking architectures.	Limited capability with complex, non-linear feature relationships.
Decision Tree	Structure is easy to visualize and explain; effectively captures complex, non-linear relationships within data.	Captures intricate patterns and hierarchical feature interactions.	Highly susceptible to over-fitting, especially when trained on noisy text data.
Random Forest	Ensemble technique composed of multiple decision trees that offer strong generalization capabilities.	Significantly reduces the risk of over-fitting and provides built-in feature importance evaluation.	Higher computational complexity compared to single decision trees.
Support Vector Machine	Highly effective in high-dimensional feature spaces and performs well even on smaller training datasets.	Excellent for high-dimensional sparse text data.	Sensitive to noisy outliers and requires careful hyper-parameter tuning for optimal performance.

3.3 Parameter Search Space

The choice of suitable parameters has a big impact on how well machine learning models function. Parameters are preset configuration settings that regulate a machine learning algorithm's learning behavior, complexity and capacity for generalization.

Table 3: Search space configuration for random search technique

Base Models	Parameter	Search Values	Possible combinations
Logistic Regression	C Penalty Solver	0.1,1,10,100 L1,L2 lib-linear, saga	16
Decision Tree	max_depth min_samples_split Criterion	5,10 2,5 gini, entropy	8
Random Forest	n_estimators max_depth max_features min_samples_split	100,200 10,20 sqrt,log2 2,5	16
Support Vector Machine	C Kernel Gamma	0.1,1,10,100 linear,polynomial scale, auto	16

3.3.1. General Model Representation

A machine learning model can be expressed as:

$$y=f(x; \theta, \lambda)$$

Where:

- x = input features
- θ = learned parameters (weights)
- λ = parameters

Interpretation: parameters λ control how parameters θ are learned.

3.3.2. Regularization Effect (Logistic Regression / SVM)

Regularization serves as a penalty mechanism that prevents models from over-fitting by discouraging overly complex coefficients. In Logistic Regression and SVM, adjusting the regularization parameter C allows the

model to strike an optimal balance between minimizing training error and maintaining a simple decision boundary that generalizes well to unseen news data.

$$\text{Min } \theta = \sum_{i=1}^n L(y_i, f(x_i; \theta)) + \lambda \|\theta\|_2$$

Where:

- L = loss function

Interpretation:

- High $\lambda \rightarrow$ Strong regularization $\rightarrow$ Under-fitting
- Low $\lambda \rightarrow$ Weak regularization $\rightarrow$ Over-fitting

3.3.3. Decision Tree Complexity

Decision Tree complexity refers to the intricate structure of the tree and its ability to capture patterns from high-dimensional text data. If a tree is too complex, it leads to over-fitting; if it is too simple, it leads to under-fitting.

$$\text{Complexity} \propto 2^{\text{max_depth}}$$

Interpretation:

- Large-max_depth $\rightarrow$ High complexity $\rightarrow$ Over-fitting
- Small max_depth $\rightarrow$ Low complexity $\rightarrow$ Under-fitting

3.3.4. Random Forest Stability

Random Forest Stability refers to the model's ability to maintain consistent and reliable classification performance across diverse, high-dimensional textual datasets.

$$\text{Error} = \text{Bias}^2 + \text{Variance}$$

$$\text{Variance} \downarrow \text{ as } n_{\text{estimators}} \uparrow$$

Interpretation: More trees $\rightarrow$ Reduced variance $\rightarrow$ Better generalization

3.3.5. SVM Decision Boundary

The SVM decision boundary is a hyperplane that separates real and fake news classes by maximizing the margin between the nearest data points of each category.

$$f(x) = \sum_{i=1}^n \alpha_i K(x_i, x) + b$$

Where:

- $K(x_i, x)$ = kernel function
- γ controls kernel spread

Interpretation:

- High $\gamma \rightarrow$ Complex boundary $\rightarrow$ Over-fitting
- Low $\gamma \rightarrow$ Smooth boundary $\rightarrow$ Under-fitting

3.4 Random Search Technique

In contrast to exhaustive search methods like Grid Search, Random Search samples a predetermined number of parameter combinations and assesses their performance. Random Search is a parameter tuning technique that randomly chooses combinations of parameter values from a predefined search space. The basic idea behind Random Search is as follows: $S = P_1 \times P_2 \times P_3 \times \dots \times P_n$ where:

- S represents the complete parameter search space
- $P_1, P_2, \dots, P_n$ represent the possible values of different parameters.

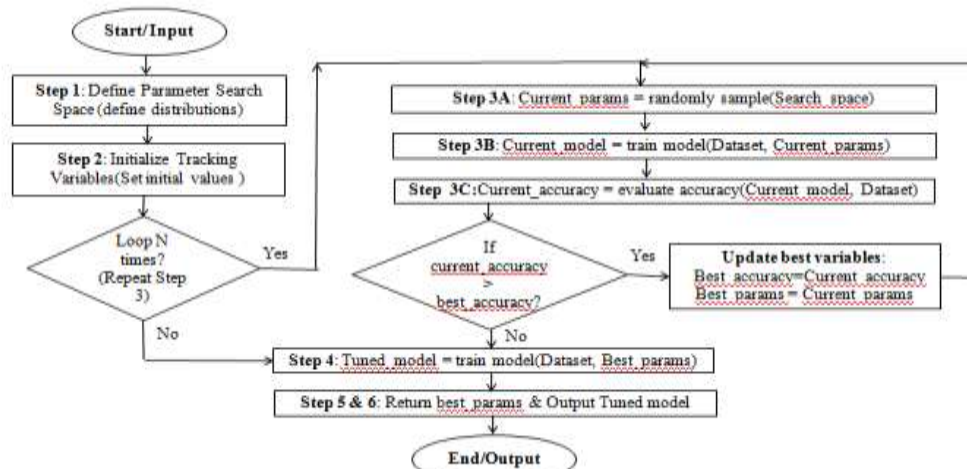


Figure 1: Workflow of Random Search Technique for Parameter Tuning

Random Search provides computational advantages because it evaluates only selected combinations rather than performing exhaustive evaluation. This approach is particularly useful when the search space contains multiple parameters and the computational cost of evaluating all possible configurations is high.

4. Result Analysis and Discussion

Using the random search method, this section effectively assesses the efficacy of tuning parameters for logistic regression, decision trees, support vector machines, and random forest base models of machine learning. By adjusting the parameters, the basis classifiers' learning capacity was enhanced and over-fitting was lessened. The quality of prediction probabilities, which will be utilized as meta-features in the ensemble approach, was improved through parameter adjustment. The experimental evaluation shows that Random Search-based systematic parameter adjustment effectively resolves baseline model limitations and maximizes individual classification performance.

Table 4: Random search-based parameter tuning results for logistic regression

Trial	Parameters			Accuracy
No.	C	Penalty	Solver	(%)
1	0.1	L1	Lb-linear	51.5
2	100	L2	Saga	52.8
3	10	L2	Saga	53.1
4	1	L1	Saga	51.7
5	10	L1	Lb-linear	51.9
6	1	L2	Lib-linear	52.4
7	100	L1	Saga	52.9
8	0.1	L2	Saga	52.2
9	100	L1	Lib-linear	52.6

Table 5: Random search-based parameter tuning results for support vector machine

Trial	Parameters			Accuracy
No.	C	Kernel	Gamma	(%)
1	0.1	Linear	Scale	51.4
2	1	Polynomial	Auto	51.6
3	100	Linear	Auto	52.5
4	10	Linear	Scale	54.2
5	10	Polynomial	Scale	53.7
6	0.1	Polynomial	Scale	51.9
7	1	Linear	Auto	52.1
8	100	Polynomial	Auto	53.0
9	1	Linear	Scale	52.8

Table 6: Random search-based parameter tuning results for decision tree

Trial	Parameters			Accuracy
No.	max_depth	min_samples_split	Criterion	(%)
1	5	2	Gini	79.1
2	10	2	gini	78.7
3	10	5	Entropy	87.0
4	5	5	Entropy	75.8
5	10	5	gini	77.2

Table 7: Random search-based parameter tuning results for random forest

Trial	Parameters				Accuracy
No.	Trees	Depth	Features	Split	(%)
1	100	10	sqrt	2	51.5
2	100	20	log2	5	50.2
3	200	20	sqrt	5	52.4
4	200	10	sqrt	2	51.5
5	100	20	Sqrt	2	51.8
6	100	10	log2	2	51.0
7	200	10	log2	5	51.9
8	200	20	log2	2	52.1
9	100	10	sqrt	5	51.6

In order to overcome these constraints, this work proposes a diagnostic-driven method that creates a mapping between hyper-parameters and performance gaps and assesses baseline models before adjusting.

4.1 Accuracy Variations Across Random Search Parameter Trials

Depending on how its parameters were set, each baseline model showed unique changes in sensitivity and accuracy during the Random Search trials. The decision trees showed the greatest sensitivity to changes in parameters. Overall, comparing these parameter combinations across trials demonstrates how regularization tweaking and particular structural depth limitations stabilize classification performance across various baseline models. Analyzing these trial changes reveals that targeted structural limitations, including tree depth and regularization scaling, are crucial for enhancing prediction quality before ensemble integration, even when linear and ensemble models preserve consistent baseline stability.

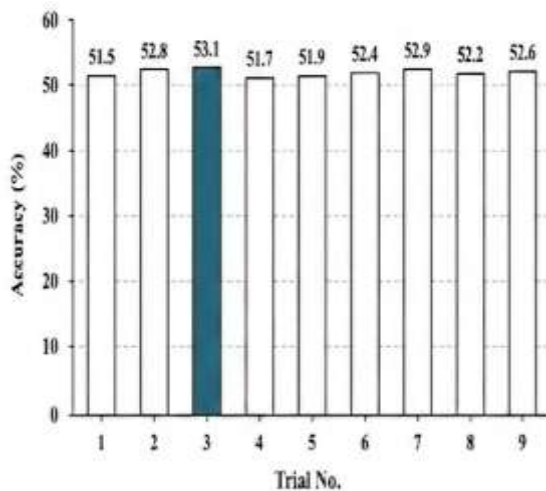


Fig 2: Accuracy Variation for LR

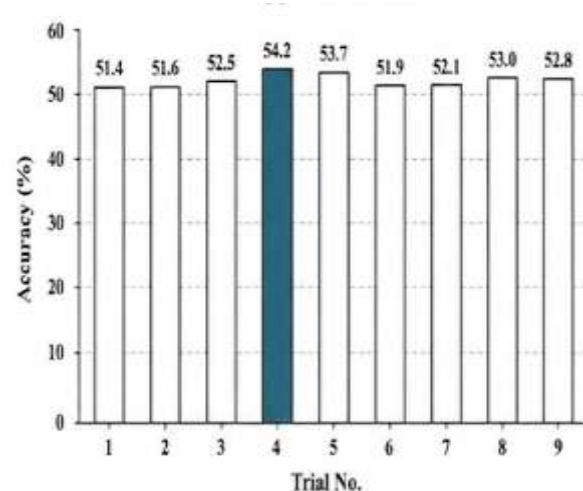


Fig 3: Accuracy Variation for SVM

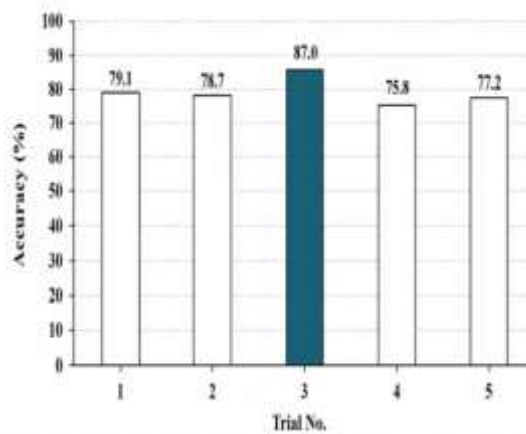


Fig 4: Accuracy Variation for DT

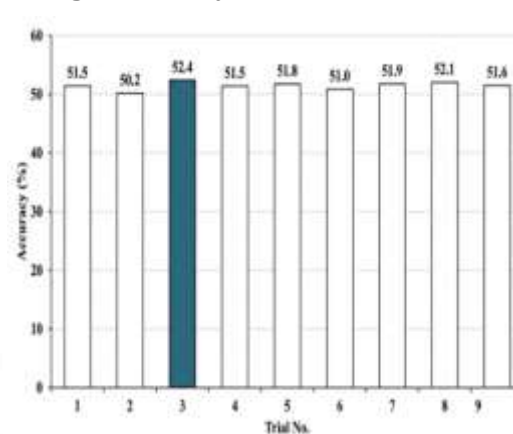


Fig 5: Accuracy Variation for RF

4.2 Parameter Combination's Influence on Model

Each classifier's ability to learn from high-dimensional TF-IDF text features is directly influenced by parameter combinations that determine model capacity, regularization strength, and feature extraction behavior. In the end, weak, baseline learners are methodically transformed into strong, well-calibrated classifiers that produce high-quality prediction probabilities necessary for downstream arranging ensemble integration by adjusting these particular parameter combinations.

Table 8: Comparative evaluation of parameter tuning with Random Search technique

Model	Parameters Combination	Remarks
Logistic Regression	C = 10, Penalty = L2, Solver = saga	Highest validation Accuracy with balanced regularization
Support Vector Machine	C=10, Kernel = Linear, Gamma = Scale	Best classification boundary for TF-IDF features with strong generalization

Decision Tree	max_depth=10 min_samples_split=5, Criterion = Entropy	Reduced over-fitting while improving information gain
Random Forest	n_estimators=200, max_depth = 20, max_features = sqrt min_samples_split = 5	Highest validation performance with lower variance and greater robustness

- **Under-fitting-** Regularization (C , λ): Under-fitting occurs when the model is too simple to capture underlying patterns in the data. This is often caused by strong regularization, where large values of λ (or small values of C) restrict model flexibility. Adjusting these parameters allows the model to better learn complex relationships.
- **Over-fitting-** Model Complexity (max_depth, C): Over-fitting arises when the model becomes excessively complex and memorizes training data. Parameters such as high max_depth in Decision Trees or large C in SVM increase model complexity. Controlling these parameters helps in reducing variance and improving generalization.
- **Generalization-** Ensemble & Kernel Parameters (n_estimators, gamma): Generalization reflects inconsistent performance on unseen data. Increasing n_estimators in ensemble models reduces variance, while tuning gamma in SVM controls decision boundary smoothness. Proper adjustment of these parameters enhances model stability and robustness.

4.3 Performance Insights from Parameter Tuning

- **Systematic tuning achieved:** A rigorous parameter tuning process conducted across four distinct baseline models logistic regression, support vector machine, decision tree and random forest to transition from broad exploratory ranges to finalized the configurations.
- **Regularization & stability:** For linear and kernel-based models logistic regression and support vector machine, a higher regularization strength coefficient $C=10$ was selected, combined with L2 regularization and a saga solver for logistic regression, ensuring stable convergence and better generalization.
- **Complexity control in tree-based models:** Both decision tree and random forest models favored deeper architectural structures max_depth = 10 and 20 respectively to capture complex patterns, while implementing strict splitting constraints min_samples_split = 5 to actively mitigate the risk of over-fitting.
- **Ensemble enhancement:** For random forest, maximizing the ensemble size n_estimators = 200 and utilizing the 'sqrt' feature split strategy established a highly robust, low-variance baseline configuration ready for stacking.

5. Conclusion and Future Work

The novelty of the work lies in its parameter tuning approach. While existing studies often report final accuracy without context, this research explains the influence of parameters on model behavior. By transforming weak base learners into optimized components, it provides a transparent and effective methodology for advancing the state of ensemble-based fake news detection. The study investigated four widely used machine learning classifiers, namely Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest, due to their complementary learning characteristics and suitability for textual classification. The integration of tuned models into an ensemble framework further boosts performance. The experimental analysis demonstrated that different classifiers require different parameter settings to achieve stable and effective performance. Future research may extend this work by investigating advanced parameter optimization techniques such as Bayesian Optimization and evolutionary algorithms. The proposed framework can also be evaluated on larger and more diverse datasets to examine its robustness across different domains.

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