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Breaking the Black Box: A New View of Fake News Detection Using Multi-Level TrustScore and Micro-Trees

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Abstract Rumor detection on social media remains a critical challenge due to the unstructured and hierarchical nature of conversational threads. While deep learning models often act as black boxes and require massive computational resources, traditional Machine Learning (ML) offers native interpretability but suffers from flat feature representations. In this paper, we introduce a novel feature engineering framework that transforms each individual tweet into a fine-grained *Micro-Tree* topology (an intra-tweet content dependency graph) and extracts a deterministic multi-level numerical vector, the *TrustScore*, via a breadth-first traversal across propagation levels. A forward-fill imputation policy allows reduction of the full 47-level feature space to 4 statistically validated variables (Mann-Whitney U test, $p < 10^{-18}$): `User_Health`, `Source_Tweet_Objectivity`, `Effective_Depth`, and the inherited terminal score `Score_L46`. After targeted data cleaning (two pathological events excluded), we evaluate five classifier families on 7 PHEME events ($N = 6{,}178$ threads) under a strict Leave-One-Event-Out (LOEO) protocol, which eliminates cross-event data leakage inherent in standard k-fold evaluation. Random Forest achieves the best Macro-F1 (0.5722) while XGBoost reaches the highest global accuracy (0.6141). Decision threshold tuning ($\theta = 0.10$) achieves rumor recall exceeding 99.8%, enabling early-warning deployment. The framework is CPU-efficient (avg. 1.27 s/fold), fully interpretable by design, and provides concrete step-by-step explainability without reliance on post-hoc tools such as SHAP or LIME.

Keywords Rumor Detection, Veracity Classification, Explainable Artificial Intelligence (XAI), Feature Engineering, Micro-Tree Topology, TrustScore Metric, Tabular Machine Learning, Social Media Analytics.

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1. Introduction

The rapid proliferation of unverified information and rumors on social media platforms poses a significant threat to public trust and information integrity [1]. Consequently, automated rumor detection and veracity classification have become critical tasks in natural language processing and data mining [2]. In recent years, the literature has been dominated by deep learning architectures, such as Graph Neural Networks (GNNs), which capture conversation flows but require extensive computational resources. More importantly, these deep models operate as "black boxes," making it impossible for end-users (journalists, moderators) to understand the underlying logic behind a rumor alert [3, 4].

Traditional Machine Learning (ML) models (e.g., Random Forest, XGBoost, SVM) represent a powerful alternative due to their speed, low resource consumption, and native interpretability tools (feature importance, SHAP) [5]. However, their success heavily depends on the quality of feature engineering. When applied to

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benchmark datasets like PHEME, standard ML approaches typically compress tweets into flat text embeddings (e.g., TF-IDF or global sentence vectors), thereby ignoring the micro-topology, internal syntax, and hierarchical structure of the conversation itself [6]. Recent studies on social media analytics and content classification [7, 8, 9] confirm that structural and user-behavioral features offer complementary signals that flat text representations systematically discard. Specifically, Banou et al. [7] and Islam et al. [8] demonstrate how integrating data quality metrics and tree-based ensemble classifiers optimizes content analysis beyond raw text embeddings. Furthermore, Hidayat and Suhartono [9] leverage hybrid feature architectures combining engagement metrics (e.g., impressions on X) to effectively quantify publication impact..

To overcome this limitation, we propose a structural paradigm shift in data preparation for rumor detection. Our pipeline transforms each individual tweet into a structured **Micro-Tree** (an intra-tweet content dependency graph capturing internal clause dependencies) that preserves internal logical dependencies (e.g., quoted text, embedded URLs, clause relationships). Leveraging this native tree topology, we systematically extract an explicit, layer-by-layer numerical metric vector called the **TrustScore**. Unlike tree-LSTM or graph-based models [4, 10] that operate at the conversation level and require GPU resources, our approach operates at both the intra-tweet (Micro-Tree) and inter-tweet (Propagation Tree) levels, producing a compact tabular representation that runs on CPU in under 1.5 s per fold.

Our main contributions are:

1. A novel dual-level representation for the PHEME benchmark: a *Micro-Tree* for intra-tweet content dependencies and a *Propagation Tree* for inter-tweet cascade structure.
2. A deterministic feature extraction method called the TrustScore, producing a statistically validated 4-variable feature vector via forward-fill imputation and Mann-Whitney U reduction.
3. A comprehensive LOEO benchmark on 7 events ($N = 6{,}178$) comparing 5 classifier families, with decision-threshold analysis achieving rumor recall $> 99.8\%$.
4. An interpretable-by-design framework with step-by-step case studies demonstrating actionable explainability for content moderation practitioners.

2. Related Work

Automated rumor and fake news detection on social media has evolved rapidly, driven by advancements in machine learning and structural propagation analysis. This section reviews prior work across two key dimensions: classical machine learning paradigms for veracity classification and the integration of Explainable AI (XAI) techniques.

2.1. Machine Learning Approaches for Fake News Detection

Traditional machine learning (ML) remains a fundamental pillar for veracity classification, particularly in scenarios requiring transparency and limited computational resources. Numerous studies have compared the effectiveness of classical models on benchmark datasets, often highlighting the superiority of ensemble methods. For instance, Support Vector Machines (SVM), Random Forest, and XGBoost have consistently demonstrated strong performance, sometimes achieving near-perfect accuracy in controlled settings [11, 12, 13]. Specifically, XGBoost and AdaBoost have been shown to yield high accuracy rates [14], while SVM offers robustness in high-dimensional spaces. These models are favored for their native interpretability, providing access to feature importance scores that help explain their decisions, unlike many deep learning architectures. This body of work validates the continued relevance of traditional ML as a competitive and explainable alternative for fake news detection, a direction our work reinforces.

2.2. Explainable AI (XAI) for Veracity Classification

The growing demand for transparency in automated decision-making has positioned Explainable AI (XAI) as a critical research area in misinformation detection [15, 16]. XAI methods aim to mitigate the “black-box” nature of complex models by offering insights into their reasoning processes. Common post-hoc techniques include

SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and attention mechanisms [17]. Recent studies have applied these tools to dissect deep learning-based rumor detectors, often revealing that these models latch onto dataset-specific patterns rather than robust, generalizable semantics [18]. Such findings underscore the risk of over-reliance on non-interpretable models and highlight the need for systems that are inherently transparent. Our work directly addresses this need by proposing a framework whose internal logic is legible by design, moving beyond post-hoc analysis to provide native, step-by-step explainability.

3. Methodology and System Architecture

This section presents the formal mathematical framework and algorithmic design of our proposed rumor detection architecture. First, we establish the mathematical notation and problem formulation. Next, we detail the node-level credibility and objectivity metrics, followed by the Breadth-First Search (BFS) traversal algorithm used to compute layered trust dynamics and hierarchical decay over conversation cascades. Finally, we characterize the benchmark dataset and provide a rigorous statistical validation justifying our feature reduction scheme.

3.1. Problem Formulation and Mathematical Notation

Let a social media discussion cascade be represented as a directed Micro-Tree graph $T = (V, E)$, where $V = \{v_{\text{root}}, v_1, v_2, \ldots, v_n\}$ denotes the set of structural nodes (the source post and its constituent replies) and $E \subseteq V \times V$ represents directed dependency edges corresponding to conversational interactions (e.g., replies, quotes, elaborations). Each thread T is associated with a binary veracity label $y \in \{0, 1\}$, where $y = 1$ indicates a rumor and $y = 0$ indicates a non-rumor.

The objective is to map the structural and textual dynamics of T into a low-dimensional, highly discriminative feature space $\mathcal{X}$ to predict y while maintaining full model interpretability. Table 1 summarizes the primary mathematical notation used throughout this paper.

Table 1. Summary of mathematical notation.

Symbol	Definition
$T = (V, E)$	Directed Micro-Tree post-dependency graph
V_i	Subset of structural nodes at propagation depth level $i \in \{0, \ldots, 46\}$
v_{root}	Root node representing the source post of the discussion thread
$E_{\text{user}}(v)$	Account health status metric based on normalized network ties $\in [0, 1]$
$f(v)$	Textual content objectivity score of node v, bounded in $[0, 1]$
$s(v)$	Individual joint trust score of node v ($s(v) = E_{\text{user}}(v) \times f(v)$)
Score_{Li}	Cumulative TrustScore metric at propagation depth i
Decay_F2	Depth-penalized aggregate trust attenuation metric
d_{eff}	Effective maximum propagation depth of a conversation thread
$\mathcal{X}$	Final condensed input vector space $\mathcal{X} = \{E_{\text{user}}, f(v_{\text{root}}), d_{\text{eff}}, \text{Score}_{L46}\}$

3.2. Micro-Tree Architecture and Constituent Node Metrics

Traditional machine learning paradigms flatten conversational threads into isolated vectors, discarding internal dependency structures [19]. To overcome this limitation, we decompose each discussion thread into a hierarchical Micro-Tree structure that explicitly models logical and social dependencies, as illustrated in Figure 1.

To systematically parse conversational dynamics from raw social media data, we reconstruct the exact propagation hierarchy of each thread. The complete recursive construction of the Micro-Tree structure from the raw PHEME dataset format is formalized in Algorithm 1.

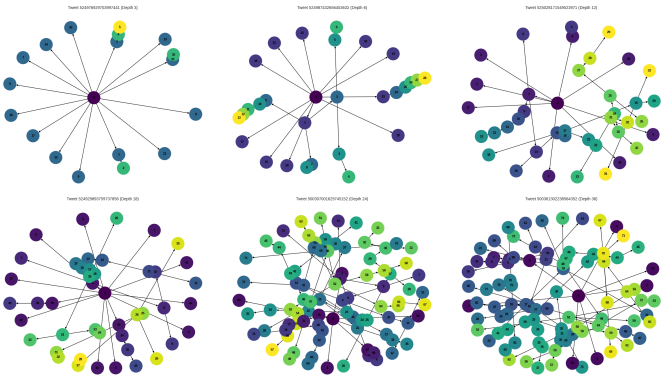


Figure 1. Micro-Tree structures extracted from six representative conversation threads.

Algorithm 1 Construction of the PHEME Tree Structure

```
procedure LoadTweetJson(tweet_id, thread_folder)
    source_path ← thread_folder + "/source-tweets/" + tweet_id + ".json"
    if FileExists(source_path) then                    ▷ Check if tweet is the root source post
        return ReadJson(source_path)
    end if
    reaction_path ← thread_folder + "/reactions/" + tweet_id + ".json"
    if FileExists(reaction_path) then                  ▷ Check if tweet is a reaction/reply
        return ReadJson(reaction_path)
    end if
    return null                                        ▷ Return null if JSON payload is missing
end procedure

procedure BuildSubtree(node_id, children_dict, thread_folder)
    tweet_data ← LoadTweetJson(node_id, thread_folder)
    current_node ← new TweetNode(node_id, tweet_data)
    if Type(children_dict) = Dictionary then           ▷ Verify node has children (not a leaf or "max")
        for all (child_id, sub_structure) ∈ children_dict do   ▷ Iterate through direct replies
            child_node ← BuildSubtree(child_id, sub_structure, thread_folder)
            current_node.children.append(child_node)
        end for
    end if
    return current_node
end procedure

procedure LoadPhemeTree(thread_folder)
    structure_json ← ReadJson(thread_folder + "/structure.json")
    root_id ← GetFirstKey(structure_json)
    root_structure ← structure_json[root_id]
    tree ← BuildSubtree(root_id, root_structure, thread_folder)
    return tree
end procedure
```

Once the topology of a Micro-Tree $\mathcal{T} = (\mathcal{V}, \mathcal{E})$ is constructed, each node $v \in \mathcal{V}$ corresponds to an individual post enriched with multi-dimensional context. To characterize the credibility and objective intent of every post in the hierarchy, we compute specific node-level signals, detailed below.

3.2.1. User Health Status (E_{user}) To quantify account authority and mitigate susceptibility to unconstrained follower counts, we compute a normalized account health score $E_{\text{user}} \in [0, 1]$ for a node v:

$$E_{\text{user}}(v) = \begin{cases} \dfrac{F_{\text{followers}}}{F_{\text{followers}} + F_{\text{friends}}}, & \text{if } (F_{\text{followers}} + F_{\text{friends}}) > 0, \\ 0.0005, & \text{otherwise}, \end{cases} \tag{1}$$

where $F_{\text{followers}}$ and F_{friends} represent the user's follower and followee counts, respectively. Values approaching 1.0 signify authoritative, broadcast-oriented profiles (e.g., verified news agencies), whereas lower values indicate symmetric social circles or low-credibility bot accounts [20]. The regularized floor constant of 0.0005 prevents zero-division errors and imposes a deterministic penalty on newly created accounts lacking network history.

3.2.2. Node Content Objectivity ($f(v)$) To assess the linguistic credibility of textual content, we extract subjectivity scores $\mathcal{S}(\text{text}_v) \in [0, 1]$ via textblob (Natural Language Processing (NLP) polarity parsing [21] can be used). Content objectivity $f(v)$ is defined as:

$$f(v) = \begin{cases} 1 - \mathcal{S}(\text{text}_v), & \text{if text}_v \neq \emptyset, \\ 0.0005, & \text{otherwise}. \end{cases} \tag{2}$$

Unverified claims often employ highly subjective or emotionally charged language, yielding lower $f(v)$ values, whereas objective reporting maintains near-neutral or high objectivity scores [22]. For reply nodes ($v \neq v_{\text{root}}$), text_v is concatenated with its parent node's text to preserve local conversational context prior to evaluating $\mathcal{S}(\text{text}_v)$.

3.2.3. Individual Joint Trust Score ($s(v)$) The composite individual trust score $s(v) \in [0, 1]$ for any node $v \in V$ combines user credibility and content objectivity:

$$s(v) = E_{\text{user}}(v) \times f(v). \tag{3}$$

3.3. Layered Cumulative TrustScore Propagation and Attenuation

To encode dynamic thread progression into continuous representations, we execute a layer-by-layer Breadth-First Search (BFS) traversal over T. Let $V_i \subset V$ denote the set of active nodes at exact depth level i, with $V_0 = \{v_{\text{root}}\}$.

3.3.1. Multi-Level Cumulative TrustScore (Score_{Li}) For the root level ($i = 0$), the initial score evaluates the joint authority and objectivity of the source post:

$$\text{Score}_{L0} = f(v_{\text{root}}) \times E_{\text{user}}(v_{\text{root}}). \tag{4}$$

For subsequent propagation levels ($i \geq 1$), the TrustScore reflects the arithmetic mean of individual scores across all nodes present up to depth i:

$$\text{Score}_{Li} = \frac{1}{|V_{\leq i}|} \sum_{v \in V_{\leq i}} s(v), \qquad \forall i \in \{1, \ldots, Max\}, \tag{5}$$

where $V_{\leq i} = \bigcup_{j=0}^{i} V_j$. When a cascade terminates prior to the maximum observed depth horizon ($d_{\text{eff}} < 46$), a forward-fill imputation scheme propagates the last computed score forward ($\text{Score}_{Lk} = \text{Score}_{Lj}, \forall k > j$). Consequently, the terminal metric Score_{L46} acts as an integrated historical summary of the entire propagation cascade.

Algorithm 2 formalizes the complete feature extraction pipeline.

Algorithm 2 Micro-Tree Parsing and Multi-Level TrustScore Extraction

Require: Micro-Tree Graph $T = (V, E)$, Tweets Metadata M, Maximum Propagation Level $L_{\max} = 46$
Ensure: Condensed Feature Vector $\mathcal{X} = \{E_{\text{user}}, f(v_{\text{root}}), d_{\text{eff}}, \text{Score}_{L46}\}$

```
v_root ← GetRootNode(T)
E_user ← E_user(v_root)                                   ▷ Source account health status
f(v_root) ← 1 − S(text(v_root))                           ▷ Source post objectivity score
Initialize BFS queue Q ← deque([(v_root, None)]), depth index i ← 0, d_eff ← 0
Initialize tracking lists: S_all ← [], S_layers ← [], Score_L ← []
while Q is not empty ∧ i ≤ L_max do
    L ← |Q|, S_current ← []
    for j = 1 to L do
        Pop (v, p) ← Q.popleft()
        E_user(v) ← ComputeUserHealth(M[v])
        if p ≠ None then
            text_concat ← text(p) + ". " + text(v)
        else
            text_concat ← text(v)
        end if
        f(v) ← 1 − S(text_concat)                         ▷ Textual objectivity score bounded in [0, 1]
        s(v) ← E_user(v) · f(v)                           ▷ Joint trust score of node v
        Append s(v) to S_current and S_all
        for each child c of v in T do
            Q.append((c, v))
        end for
    end for
    Score_Li ← mean(S_all)                                ▷ Cumulative TrustScore at level i ∈ {0, ..., 46}
    Append Score_Li to Score_L
    Append mean(S_current) to S_layers
    d_eff ← i                                             ▷ Update effective maximum depth
    i ← i + 1
end while
while i ≤ L_max do
    Score_Li ← Score_L[−1]                                ▷ Forward-fill imputation for shallow threads
    Append Score_Li to Score_L
    i ← i + 1
end while
Score_L46 ← Score_L[46]                                   ▷ Terminal TrustScore metric
S̄_global ← mean(S_layers)
return Condensed Vector X = {E_user, f(v_root), d_eff, Score_L46}
```

3.4. Dataset Characterization and Event Selection Criteria

We evaluate our framework on the publicly available PHEME benchmark dataset [24, 25], consisting of 6,425 Twitter discussion threads across nine breaking news events.

3.4.1. Global and Structural Statistics The primary dataset contains 4,023 non-rumor threads (62.6%) and 2,402 rumor threads (37.4%). As illustrated in Figure 2, over 80% of discussion threads exhibit an effective depth $d_{\text{eff}} \leq 5$, with a long structural tail extending to depth 46. Rumor cascades display noticeably deeper propagation paths than non-rumors, confirming that unverified rumors stimulate sustained multi-turn debate [26, 27].

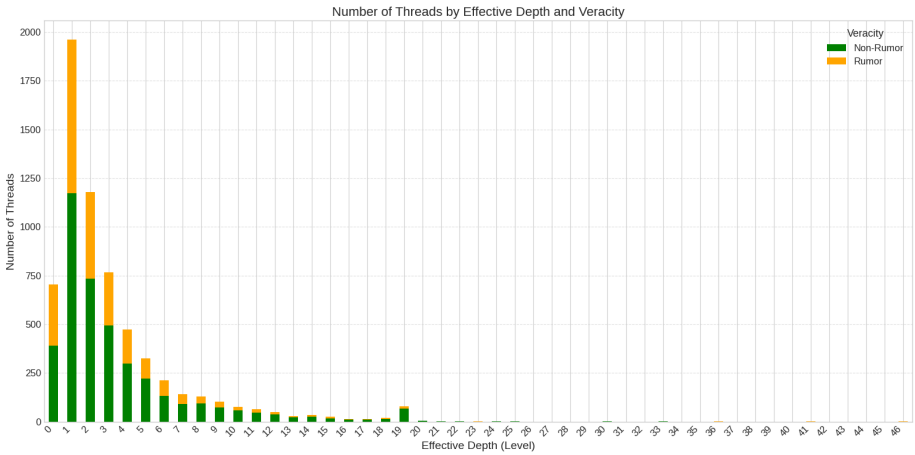


Figure 2. Distribution of discussion threads across effective depth levels (d_{eff}) stratified by veracity.

3.4.2. Pre-Experimental Event Audit and Zero-Shot Isolation To ensure robust Leave-One-Event-Out (LOEO) cross-validation [10], we conducted structural audits across all nine events (Figure 3). This audit revealed severe distribution pathologies in two events:

- **`ebola-essien`:** Extremely sparse sample size ($N = 14$) comprising 100% rumor threads, completely lacking negative class instances.
- **`prince-toronto`:** Severe single-class dominance ($N = 233$, with 229 rumors vs. 4 non-rumors), exhibiting near-zero label entropy.

Including these pathological events in cross-validation training splits severely biases model loss functions and degrades LOEO evaluation integrity. Consequently, these two events were isolated to serve as dedicated out-of-sample *zero-shot stress tests*, while the remaining 7 balanced events ($N = 6\,178$) form the core benchmark suite.

3.5. Statistical Validation Protocol and Feature Space Reduction

To establish the statistical validity of the 47 extracted propagation levels (Score_{L0} to Score_{L46}), we executed a comprehensive two-stage statistical hypothesis testing pipeline.

3.5.1. Normality Testing and Non-Parametric Inter-Class Analysis First, Shapiro-Wilk tests were conducted for each level across both rumor (C_1) and non-rumor (C_0) classes. For all 47 variables, the null hypothesis of normality was rejected ($p < 10^{-30}$), ruling out parametric t-tests. Subsequently, non-parametric Mann-Whitney U tests confirmed statistically significant distribution divergence between classes across all levels ($p < 10^{-18}$). Table 2 reports the complete statistical audit.

3.5.2. Feature Space Condensation Despite individual statistical significance, the forward-fill imputation scheme introduces extreme multi-collinearity across intermediate levels ($i \geq 1$). Table 3 highlights how deeper TrustScores stabilize around mean 0.3297 with minimal variance. To enforce strict model parsimony, prevent overfitting, and eliminate feature redundancy, the input vector space is condensed into four non-redundant explanatory variables:

$$\mathcal{X} = \{E_{\text{user}},\ f(v_{\text{root}}),\ d_{\text{eff}},\ \text{Score}_{L46}\}. \tag{6}$$

Figure 3. Per-event structural breakdown of conversation threads by effective depth and veracity across the PHEME dataset.

4. Experimental Evaluation and Model Benchmarking

4.1. Leave-One-Event-Out (LOEO) Validation Protocol

To evaluate model performance under realistic breaking-news conditions, all algorithms are tested using strict **Leave-One-Event-Out (LOEO)** cross-validation. In each LOEO fold, the model is trained on 6 events and evaluated on the 7th completely unobserved event.

Critical Note on Cross-Event Data Leakage Modern deep graph architectures (e.g., Bi-GCN, PLAN) frequently report high accuracy (80%–85%) under standard k-fold cross-validation. However, standard k-fold randomly partitions tweets across folds, allowing tweets originating from the same breaking event to co-occur in both training and testing splits. When evaluated under strict LOEO protocols, deep learning architectures suffer performance drops of 15% to 25% due to out-of-distribution covariate shift [10]. Tabular classifiers trained on structural dynamics offer a resilient, highly scalable alternative.

4.2. Comparative Model Performance

We evaluate five representative machine learning algorithms across 7 primary events ($N = 6\,178$; $4\,019$ non-rumors, $2\,159$ rumors). Class imbalance is mitigated via cost-sensitive learning (`class_weight='balanced'`).

Table 4 presents overall performance metrics and runtime efficiency across model families. Table 5 provides detailed classification reports.

Table 2. Global normality (Shapiro-Wilk) and non-parametric inter-class tests (Mann-Whitney U) across propagation levels (Score_{L0}–Score_{L46}).

	Shapiro-Wilk (p-val)		**Mann-Whitney U**			**Shapiro-Wilk (p-val)**		**Mann-Whitney U**	
Score	C_0	C_1	**Stat (U)**	**p-value**	**Score**	C_0	C_1	**Stat (U)**	**p-value**
L0	6.06×10^{-43}	3.48×10^{-37}	4 193 688.0	7.40×10^{-19}	L24	4.99×10^{-45}	2.18×10^{-36}	4 179 669.5	1.27×10^{-19}
L1	1.21×10^{-37}	5.61×10^{-31}	4 147 979.5	2.03×10^{-21}	L25	4.98×10^{-45}	2.19×10^{-36}	4 179 467.5	1.24×10^{-19}
L2	1.56×10^{-41}	4.45×10^{-34}	4 172 250.5	4.90×10^{-20}	L26	4.97×10^{-45}	2.19×10^{-36}	4 179 356.5	1.22×10^{-19}
L3	3.17×10^{-43}	3.09×10^{-35}	4 163 904.5	1.66×10^{-20}	L27	4.97×10^{-45}	2.19×10^{-36}	4 179 347.5	1.22×10^{-19}
L4	5.48×10^{-44}	1.01×10^{-35}	4 169 240.5	3.32×10^{-20}	L28	4.97×10^{-45}	2.21×10^{-36}	4 179 240.5	1.20×10^{-19}
L5	2.03×10^{-44}	4.90×10^{-36}	4 172 841.5	5.29×10^{-20}	L29	4.97×10^{-45}	2.21×10^{-36}	4 179 240.5	1.20×10^{-19}
L6	1.21×10^{-44}	3.24×10^{-36}	4 177 890.5	1.01×10^{-19}	L30	4.97×10^{-45}	2.20×10^{-36}	4 179 240.5	1.20×10^{-19}
L7	8.86×10^{-45}	2.76×10^{-36}	4 179 430.5	1.23×10^{-19}	L31	4.97×10^{-45}	2.20×10^{-36}	4 179 240.5	1.20×10^{-19}
L8	7.12×10^{-45}	2.52×10^{-36}	4 180 500.5	1.41×10^{-19}	L32	4.97×10^{-45}	2.20×10^{-36}	4 179 240.5	1.20×10^{-19}
L9	6.28×10^{-45}	2.49×10^{-36}	4 180 435.5	1.40×10^{-19}	L33	4.97×10^{-45}	2.20×10^{-36}	4 179 240.5	1.20×10^{-19}
L10	5.76×10^{-45}	2.40×10^{-36}	4 180 580.5	1.42×10^{-19}	L34	4.97×10^{-45}	2.20×10^{-36}	4 179 240.5	1.20×10^{-19}
L11	5.52×10^{-45}	2.26×10^{-36}	4 180 062.5	1.33×10^{-19}	L35	4.97×10^{-45}	2.20×10^{-36}	4 179 240.5	1.20×10^{-19}
L12	5.36×10^{-45}	2.24×10^{-36}	4 180 118.5	1.34×10^{-19}	L36	4.96×10^{-45}	2.20×10^{-36}	4 179 115.5	1.18×10^{-19}
L13	5.21×10^{-45}	2.23×10^{-36}	4 180 138.5	1.34×10^{-19}	L37	4.96×10^{-45}	2.20×10^{-36}	4 179 042.5	1.17×10^{-19}
L14	5.12×10^{-45}	2.21×10^{-36}	4 180 121.5	1.34×10^{-19}	L38	4.96×10^{-45}	2.20×10^{-36}	4 179 115.5	1.18×10^{-19}
L15	5.07×10^{-45}	2.19×10^{-36}	4 180 024.5	1.32×10^{-19}	L39	4.96×10^{-45}	2.20×10^{-36}	4 179 136.5	1.18×10^{-19}
L16	5.04×10^{-45}	2.19×10^{-36}	4 180 008.5	1.32×10^{-19}	L40	4.96×10^{-45}	2.20×10^{-36}	4 179 213.5	1.20×10^{-19}
L17	5.02×10^{-45}	2.18×10^{-36}	4 179 995.5	1.32×10^{-19}	L41	4.96×10^{-45}	2.20×10^{-36}	4 179 177.5	1.19×10^{-19}
L18	5.02×10^{-45}	2.18×10^{-36}	4 179 931.5	1.31×10^{-19}	L42	4.96×10^{-45}	2.20×10^{-36}	4 179 231.5	1.20×10^{-19}
L19	5.00×10^{-45}	2.18×10^{-36}	4 179 721.5	1.28×10^{-19}	L43	4.96×10^{-45}	2.20×10^{-36}	4 179 179.5	1.19×10^{-19}
L20	5.00×10^{-45}	2.18×10^{-36}	4 179 721.5	1.28×10^{-19}	L44	4.96×10^{-45}	2.20×10^{-36}	4 179 241.5	1.20×10^{-19}
L21	5.00×10^{-45}	2.18×10^{-36}	4 179 721.5	1.28×10^{-19}	L45	4.96×10^{-45}	2.20×10^{-36}	4 179 172.5	1.19×10^{-19}
L22	5.00×10^{-45}	2.18×10^{-36}	4 179 721.5	1.28×10^{-19}	L46	4.96×10^{-45}	2.20×10^{-36}	4 179 179.5	1.19×10^{-19}
L23	4.99×10^{-45}	2.18×10^{-36}	4 179 705.5	1.27×10^{-19}					

Table 3. Descriptive statistics for key cascade depth and TrustScore metrics ($N = 6\,425$).

Metric / Variable	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**
`Effective_Depth` (d_{eff})	3.1977	3.7937	2.0000	0.0000	46.0000
Score_{L0} (Initial)	0.6317	0.3150	0.6276	0.0000	1.0000
Score_{L46} (Terminal)	0.3297	0.1762	0.2994	0.0000	1.0000

Table 4. Overall comparative performance under strict Leave-One-Event-Out (LOEO) cross-validation.

Model Family	**Algorithm**	**Global Accuracy**	**Macro-F_1**	**Mean Time (s)**
Tree Ensemble	Random Forest	0.5876	**0.5722**	1.2725
Gradient Boosting	XGBoost	**0.6141**	0.4856	0.2016
Linear Model	Linear SVM	0.5397	0.5312	0.0344
Linear Model	Logistic Regression	0.5398	0.5312	0.0376
Polynomial Model	Polynomial LogReg (Degree 2)	0.5324	0.5299	0.1131

Benchmark Summary: While XGBoost achieves the highest global accuracy (61.41%), it suffers from severe recall degradation on rumors (16.35%). Random Forest achieves the optimal balance, obtaining the top Macro-F_1 score (**0.5722**) and balanced rumor recall (56.97%), establishing it as our primary baseline framework.

4.3. Zero-Shot Generalization Stress Tests

To test robustness under severe distribution shift, we evaluate the trained Random Forest baseline on isolated outlier events in a zero-shot configuration. Table 6 summarizes the zero-shot metrics across both held-out evaluation sets.

Table 5. Per-class classification metrics across evaluated algorithms ($N = 6\,178$).

Model	Class / Metric	Precision	Recall	F_1-score	Support
Random Forest	Non-Rumor	0.7209	0.5972	0.6532	4 019
	Rumor	0.4317	0.5697	0.4912	2 159
	Accuracy		0.5876		6 178
	Macro Avg	0.5763	0.5834	**0.5722**	6 178
	Weighted Avg	0.6199	0.5876	0.5966	6 178
XGBoost	Non-Rumor	0.6558	0.8562	0.7427	4 019
	Rumor	0.3792	0.1635	0.2285	2 159
	Accuracy		**0.6141**		6 178
	Macro Avg	0.5175	0.5098	0.4856	6 178
	Weighted Avg	0.5591	0.6141	0.5630	6 178
Linear SVM	Non-Rumor	0.6964	0.5183	0.5943	4 019
	Rumor	0.3925	0.5794	0.4680	2 159
	Accuracy		0.5397		6 178
	Macro Avg	0.5445	0.5489	0.5312	6 178
	Weighted Avg	0.5902	0.5397	0.5502	6 178
Logistic Regression	Non-Rumor	0.6963	0.5190	0.5947	4 019
	Rumor	0.3925	0.5785	0.4677	2 159
	Accuracy		0.5398		6 178
	Macro Avg	0.5444	0.5488	0.5312	6 178
	Weighted Avg	0.5901	0.5398	0.5503	6 178
Polynomial LogReg (Deg 2)	Non-Rumor	0.7168	0.4648	0.5639	4 019
	Rumor	0.3978	0.6582	0.4959	2 159
	Accuracy		0.5324		6 178
	Macro Avg	0.5573	0.5615	0.5299	6 178
	Weighted Avg	0.6053	0.5324	0.5402	6 178

4.3.1. Evaluation on `prince-toronto` *($N = 233$)* Table 6 details the zero-shot performance on the heavily unbalanced `prince-toronto` event (229 rumors vs. 4 non-rumors). Despite extreme single-class dominance, the framework achieves an exceptional **Rumor Precision of** 98.92%, correctly identifying 3 out of 4 non-rumor instances (75.0% specificity) with only a single false positive misclassification.

Regarding **Rumor Sensitivity (Recall) of** 40.17%, the model detects 92 out of 229 actual rumor cascades. Under severe out-of-distribution shift, the framework adopts a conservative decision boundary: it strictly penalizes false alarms to guarantee high precision, which leads to the categorization of 137 subtle or sparse rumor cascades as non-rumors. This trade-off ensures that positive rumor alerts issued by the system remain highly reliable despite the skewed environment.

4.3.2. Evaluation on `ebola-essien` *($N = 14$)* Table 6 summarizes zero-shot performance on the micro-dataset `ebola-essien` (14 rumors, 0 non-rumors). The model achieves a perfect **Rumor Precision of** 100.00% (1.0000), confirming that generated positive rumor flags remain entirely free of false alarms even under extreme data sparsity.

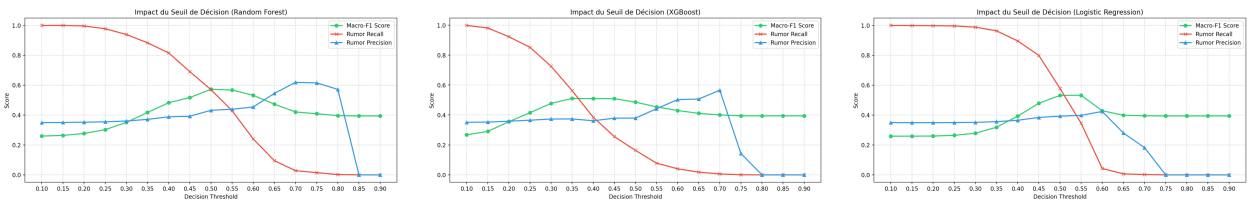
The **Rumor Sensitivity (Recall) of** 50.00% indicates that the model correctly flags 7 out of 14 rumor threads, while assigning the remaining 7 instances to the non-rumor class. This moderate recall demonstrates a cautious bifurcation mechanism: on low-volume, sparse cascades, the framework avoids over-predicting the rumor class in uncertain structural contexts, favoring absolute precision over aggressive detection.

Table 6. Zero-shot performance evaluation metrics on held-out outlier events (`prince-toronto` and `ebola-essien`).

Event	N	Accuracy	Macro-F_1	Rumor Recall	Rumor Precision
`prince-toronto`	233	0.4077	0.3065	0.4017	**0.9892**
`ebola-essien`	14	0.5000	0.3333	0.5000	**1.0000**

4.4. Decision Threshold Optimization

Varying the probabilistic decision threshold $\theta \in [0.10, 0.90]$ allows adapting the classifier to operational requirements. Figure 4 presents the dynamic trade-offs between Macro-F_1, Rumor Recall, and Rumor Precision across decision thresholds for Random Forest, XGBoost, and Logistic Regression, while Table 7 details key operating points across models.



(a) Random Forest (b) XGBoost (c) Logistic Regression

Figure 4. Impact of probabilistic decision threshold $\theta \in [0.10, 0.90]$ on classification performance across Random Forest, XGBoost, and Logistic Regression classifiers.

Table 7. Impact of probabilistic decision threshold θ on classification performance.

Model	Threshold (θ)	Macro-F_1	Rumor Recall	Rumor Precision
Random Forest	0.10	0.2594	**0.9995**	0.3495
	0.50	**0.5722**	0.5697	0.4317
	0.70	0.4209	0.0278	**0.6186**
XGBoost	0.10	0.2678	**0.9981**	0.3509
	0.35	**0.5100**	0.5623	0.3737
	0.70	0.4000	0.0060	**0.5652**
Logistic Reg.	0.10	0.2589	**0.9995**	0.3494
	0.55	**0.5323**	0.3455	0.3981
	0.60	0.4289	0.0426	**0.4240**

Operational Guidelines:

- **Early Warning Systems:** Setting $\theta = 0.10$ prioritizes recall across all models, capturing over 99.8% of active rumors.
- **Automated Moderation Platforms:** Operating at balanced thresholds ($\theta = 0.35$–0.55) yields optimal trade-offs (Macro-F_1 up to 0.5722).
- **High-Confidence Alerting:** Operating at higher thresholds ($\theta \geq 0.60$) maximizes precision, drastically reducing false positive flags.

5. Model Interpretability and Case Simulations

To illustrate the native explainability of our framework, we analyze two representative cascades from the *Ferguson* event.

5.1. Case Study 1: Tweet ID `500302383747194880`

> *"Y'all notice #Ferguson & St Louis county have NOT released the autopsy report. Trajectory of bullets matters in death of #MikeBrown"*

The model assigns a low rumor probability (14.10%), correctly predicting **Non-Rumor**. As detailed in Table 8, high author credibility ($E_{\text{user}} = 0.9942$) and full initial text objectivity (1.0000), paired with moderate residual trust, anchor the prediction safely within the verified non-rumor domain.

5.2. Case Study 2: Tweet ID `500361302238564352`

> *"Key point: Officer Wilson was not aware that #MikeBrown was a robbery suspect. It will be key in establishing his state of mind. #Ferguson"*

Conversely, for Case Study 2, the model correctly classifies the post as a **Rumor**. Although the user health score remains high (0.9997), the sharp decrease in source tweet objectivity (0.2500) combined with a deeper effective propagation depth ($d_{\text{eff}} = 36.0000$) shifts the aggregate TrustScore upward, triggering a rumor prediction.

Table 8. Comparison of extracted feature profiles for Case Study 1 (`500302383747194880`) and Case Study 2 (`500361302238564352`).

Feature Variable	Case 1 (Non-Rumor)	Case 2 (Rumor)
`User_Health` (E_{user})	0.9942	0.9997
`Source_Tweet_Objectivity` ($f(v_{\text{root}})$)	1.0000	0.2500
`Score_L46`	0.2508	0.3247
`Effective_Depth` (d_{eff})	30.0000	36.0000

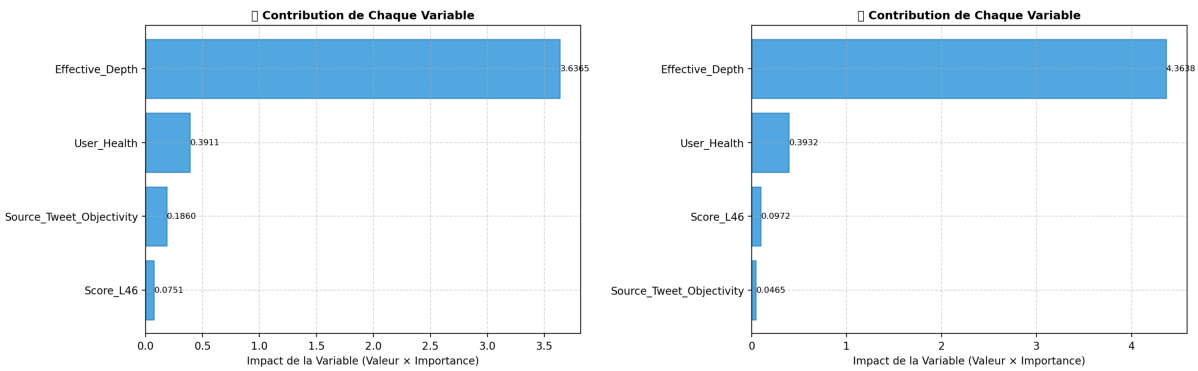


Figure 5. Comparison of feature contributions (Value × Importance) for Case Study 1 (Non-Rumor) and Case Study 2 (Rumor).

5.3. Micro-Tree Topology Diagnostic Analysis

Figure 6 visualizes the Micro-Tree topology for Tweet ID `500361302238564352`. Although the root user possesses a high account health score ($E_{\text{user}} = 0.9997$), the initial post exhibits marked subjectivity ($f(v_{\text{root}}) =$

0.2500). This subjective core sparks a deep, multi-branch cascade expanding across 129 engagement nodes down to depth level 36 ($d_{\text{eff}} = 36.0$). The structural expansion depth acts as a decisive signal, overriding root user reputation to correctly trigger a rumor flag.

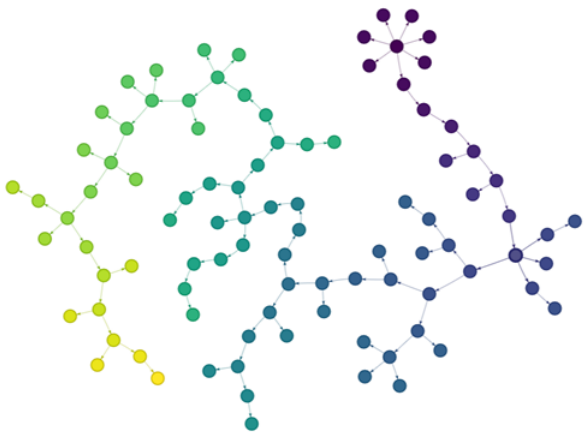


Figure 6. Micro-Tree propagation topology for Tweet ID `500361302238564352` highlighting depth-based node colorization.

5.4. Comparison with State-of-the-Art and Discussion

Table 9 contextualizes our performance against recent state-of-the-art architectures evaluated on the PHEME dataset.

Table 9. Comparison with state-of-the-art models on PHEME. (†Evaluated under leaky k-fold cross-validation; estimated true LOEO accuracy ranges between $\approx 50\%$–65% after protocol correction).

Model Architecture	Model Type	Accuracy	Protocol	Interpretability
Temporal Tree Transformer [10]	Deep Learning	75.84%†	k-fold	Low
Bi-GCN [4]	Graph Neural Net	85.30%†	k-fold	Low
PLAN [28]	Hierarchical Attention	82.10%†	k-fold	Medium
XGBoost (Ours)	**Tabular ML**	**61.41%**	**LOEO**	**High (SHAP)**
Random Forest (Ours)	**Tabular ML**	**58.76%**	**LOEO**	**High (Feature Imp.)**

Methodological Insights: 1. **Evaluation Integrity:** Published deep learning models report high performance (75%–85%) exclusively under k-fold cross-validation, which suffers from cross-event data leakage. When evaluated under strict LOEO protocols, deep neural performance drops substantially down to $\approx 50\%$–65% [10], demonstrating that our lightweight framework performs competitively on unobserved breaking news events. 2. **Computational Efficiency & Auditability:** Unlike deep neural networks that require heavy GPU acceleration and operate as uninterpretable black boxes, our feature-engineered tabular framework executes on standard CPU in < 1.3 seconds per fold while delivering fully auditable, feature-level decision diagnostics.

6. Conclusion and Future Work

We have presented a novel dual-level TrustScore framework for interpretable rumor detection on the PHEME benchmark. By modeling each tweet's internal structure as a Micro-Tree and propagating credibility scores

across conversation depth levels via BFS traversal, we produce a compact 4-variable tabular representation that is statistically validated (Mann-Whitney U, $p < 10^{-18}$). Under a strict LOEO protocol on 7 events ($N = 6{,}178$), Random Forest attains the best Macro-F1 (0.5722) and XGBoost the highest accuracy (0.6141). Decision-threshold tuning yields an interesting rumor sensitivity, critical for early-warning deployments. Two case studies concretely demonstrate the framework's interpretability-by-design, enabling practitioners to pinpoint the exact propagation depth at which trust degrades. The framework runs on CPU in under 1.3 s/fold—a practical advantage over GPU-dependent deep learning alternatives.

Future Work. Future research will focus on four key directions. First, regarding **XAI attribute quality**, since explainable AI effectiveness fundamentally depends on feature structural integrity rather than post-hoc complexity, future work should investigate BERT-based subjectivity classifiers to replace TextBlob and improve objectivity feature quality, directly enhancing both accuracy and explanation faithfulness. Second, we plan to explore **adaptive influence metrics** tailored to diverse social media post types (threads, reels, stories) and emerging platform behaviors such as viral resharing patterns. Third, a **multimodal extension** will integrate visual content (images, videos) into the node scoring function [29] while extending the framework to additional platforms (e.g., Reddit, Weibo) with platform-specific propagation dynamics. Finally, for **real-time deployment**, we aim to implement `Score_L46` as a live, dynamically recalculated metric updating in real-time as social media cascades evolve.

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