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Robust Trust Optimization in Social Graphs: Centrality-Aware GNNs with Genetic Optimization

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Abstract

Precisely evaluating trust inside social networks is essential for recognizing reliable users amid chaotic and varied interactions. This research introduces a triadic hybrid model that integrates structural centrality measures, a Centrality-Aware Graph Attention Network (CA-GAT), and Genetic Algorithm (GA) optimization. At the outset, centrality metrics degree, closeness, betweenness, eigenvector, and PageRank are standardized and integrated to produce a comprehensible initial structural trust measure. Upon application to a processed graph derived from Epinions data, which consists of 4,039 nodes and 76,879 edges, the most robust individual centrality baseline attained an ROC-AUC of 0.67. The CA-GAT model improved the structural depiction and elevated the ROC-AUC to 0.83, thereby pinpointing 3,360 nodes that exceeded the trust threshold. Following this, a GA-driven optimization phase further refined the final selection of reliable nodes, identifying 3,005 nodes and elevating the ROC-AUC to 0.85. Ablation analysis using five arbitrary initial seeds yielded 0.83 ± 0.01 for the CA-GAT model and 0.85 ± 0.01 for the combined model (CA-GAT+GA). The findings suggest that integrating interpretable graph-based initial metrics, attention-driven optimization techniques, and evolutionary optimization can improve the precision of trust classification in social networks.

1. Introduction

Trust evaluation is a fundamental requirement in large-scale social graph networks, where users continuously interact through noisy, heterogeneous, and often When faced under adversarial conditions, trust evaluation becomes vital in several domains including recommenders, fraud detection, information sharing, influence analysis, and routing in decentralized and IoT-enabled networks. However, modeling trust in such networks is inherently challenging due to incomplete observations, dynamic interactions, and the susceptibility of social graphs to manipulation strategies such as fake In the context of attacks, Sybil attacks, and trust games. Trust evaluation systems, which are reliable enough to distinguish between trustworthy and untrustworthy individuals, are needed here. The first generation of trust evaluation methods was based on graph theory and the concept of centrality of vertices. These techniques use the structure of social networks for trust evaluation, assuming that central and well-connected, or well-positioned nodes are more reliable. Centrality-based models are attractive due to their simplicity, transparency, and low computational overhead, making them suitable for large-scale networks. Nevertheless, these approaches are limited to static structural information and fail to capture contextual interaction patterns, higher-order dependencies, and semantic relationships between users, often leading to biased trust estimates that overemphasize hubs or bridge nodes regardless of their actual trustworthiness.

To overcome the limitations of purely structural methods, learning-based techniques—particularly Graph Neural Networks (GNNs) have been proposed to predict trust. GNN-based models aggregate information at multiple-hop neighborhoods and learn latent node representations that encode both topology and interaction patterns. Among these, Graph Attention Networks (GATs) dynamically

assign importance weight to their neighbor nodes for efficient information exchange. and better discriminative performance. Trust-aware GNN approaches add on to this framework by utilizing propagation rules, robust techniques or explain ability constraints. Despite their expressive power, GNN-based trust models often suffer from reduced interpretability, sensitivity to label sparsity, and instability under distribution shifts, especially when deployed across networks with diverse structural characteristics.

Despite significant progress, several challenges remain unresolved in trust evaluation research. Real-world trust datasets are typically characterized by severe class imbalance, sparse and noisy labels, and heterogeneous trust semantics across platforms. Moreover, social graphs exhibit skewed degree distributions and high structural variability, which can destabilize learning-based models. Existing methods either rely heavily on handcrafted heuristics or require extensive supervision and hyper parameter tuning, limiting their generalizability and robustness. Additionally, most current frameworks treat trust estimation and node selection as separate tasks, lacking a unified pipeline that jointly refines trust representations and optimizes global trust rankings.

To address these challenges, this paper proposes a novel three-stage hybrid trust evaluation framework that integrates interpretable structural features, attention-based graph learning, and evolutionary optimization. First, multiple normalized centrality measures are used to initialize node-level trust scores, providing transparent and auditable structural priors. Second, a Centrality-Aware Graph Attention Network (CA-GAT) explicitly injects these features into the attention mechanism, enabling topology-informed representation learning and robust trust refinement. Finally, a Genetic Algorithm (GA) formulates trust optimization as a top-k node selection problem, calibrating trust fusion and identifying the most reliable nodes through global search. This hybrid design balances interpretability, learning capacity, and robustness, while remaining scalable to large and heterogeneous social networks.

The main contributions of this work are summarized as follows:

A centrality-aware trust modeling framework that explicitly integrates interpretable graph centrality measures into attention-based GNNs for node-level trust evaluation.

A hybrid CA-GAT architecture that refines initial trust estimates through topology-informed attention and neighborhood aggregation.

A Genetic Algorithm–based trust optimization strategy that formulates trust refinement as a top-k node selection problem and optimizes global trust objectives.

Comprehensive experimental validation on multiple real-world trust datasets, demonstrating consistent improvements over state-of-the-art centrality-based and GNN-based methods.

Robustness and scalability analysis, supported by ablation studies and multi-seed evaluations, confirming the effectiveness of the evolutionary optimization stage.

Related Work

The literature can be grouped into three sections:

2.1 Centrality metrics for trust calculation

Degree centrality specifies direct connectivity, closeness measures average distance to all other connected nodes, and betweenness centrality quantifies the role of a node as an intermediary in information flow [1,5,6]. Eigenvector and PageRank further account for the influence of neighbors [7]. These metrics are used to initiate trust scores but can't capture the higher structure of patterns or temporal dynamics.

2.2 GNN-based Trust Models

Graph Neural Networks (GNNs) improve trust evaluation by consolidating data from multi-hop neighborhoods. The Graph Attention Network (GAT) [2] uses self-attention mechanisms to ascertain the significance of adjacent nodes. Expanding on this concept, Trust GNN [8] encapsulates the propagative and compositional aspects of trust, while Trust Guard [9] enhances resilience and clarity in dynamic and adversarial environments. These methodologies illustrate the significance of acquired graph representations; nevertheless, they do not explicitly use traditional centrality metrics as structural priors, as in the suggested CA-GAT paradigm.

2.3 Metaheuristic Node Selection

Combinatorial tasks on graphs, such as determining the most influential nodes, have been tackled with metaheuristic techniques, including Genetic Algorithm (GA) [3,4], Particle Swarm Optimization (PSO) [10], and Ant Colony Optimization (ACO) [11]. More recent hybrid models like PSOGA-CL merge GNN-derived embeddings with PSO and GA operators to accelerate community detection and improve convergence [12]. While GAs are especially adept at encoding fixed-size subsets via custom fitness function, existing workflows typically depend on static trust scores or manually designed heuristics, lacking a unified pipeline that trains representations and selects nodes in an end-to-end style.

2.4 Comparative Analysis

Table 1. ROC-AUC comparison across methods and the proposed approach.

Approach	ROC-AUC	Dataset	Advantage	Limitation
Degree Centrality [1]	0.65	Epinions	Simple and low cost	Multi-hop influence
Closeness Centrality [5]	0.62	Advogato	Capture reachability	Disconnected Components
Betweenness Centrality [6]	0.60	Advogato	Identifies bridge nodes	High computational complexity
Page Rank [7]	0.67	Epinions	Accounting neighbour importance	Damping with tuning
GAT [2]	0.78	Epinions	Adaptive	No centrality prior
TrustGNN [8]	0.78	Epinions	Predictive	Supervised only
TrustGuard [9]	0.80	Epinions	Explainable	Scalability
PSOGA-CL [12]	Speedup +15%	---------	Faster convergence	Increase system complexity
Proposed System	0.85	Epinions	End-to-end integration,	Higher compute and tuning cost

			interpretabl e	

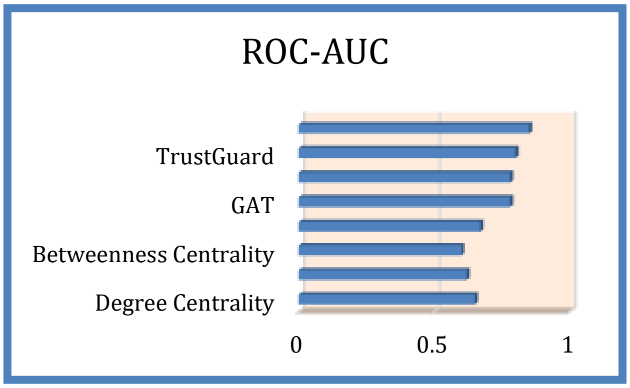


Figure (1) ROC-AUC comparison across methods

3. Data and Pre-processing

3.1 Datasets

- Epinions (trust/distrust). A directed, signed social graph of product reviewers. We use our cleaned subset comprising 4,039 nodes and 76,879 edges (details below). Links encode trust (positive) or distrust (negative/absent).
- Advogato (graded trust). A developer community where users endorse others at discrete levels (observer/apprentice/journeyer/master). Edges are directed and reflect graded trust.
- Film Trust (trust + ratings). A movie-ratings platform with asymmetric trust links between users and user–item ratings, enabling evaluation when social trust coexists with behavioral signals.

3.2 Data Cleaning and Label Construction

- Remove self-loops and duplicate edges.
- Trust annotations are initially established on directed edges inside the unprocessed datasets: In Epinions, trust relationships are represented by 1, while distrust relationships are denoted by 0. AUTHOR VERIFICATION NECESSARY: if unmonitored/absent edges were classified as class 0 during the training phase, specify the precise negative-sampling criterion. In Advogato, graded trust relationships are converted to binary form utilizing a threshold determined from the validation set. AUTHOR INPUT NEEDED: specify the precise threshold and the correspondence of each trust level. For Film Trust, AUTHOR INPUT NEEDED: clarify the method by which social trust connections and rating data were transformed into the oversight utilized by the model. Node attributes are derived from normalized degree, proximity, betweenness, eigenvector centrality, and PageRank metrics within each dataset. Forecasting assignment and label creation for nodes. The suggested architecture generates a trust score for each node, after which the GA selects the top-k most trusted nodes. AUTHOR INPUT NEEDED: detail the precise methodology employed to transform the edge-level trust annotations into the node-level targets utilized by the binary cross-entropy loss in Eq. (7), encompassing the aggregation rule, threshold, and handling of nodes with inadequate identified edges. This data is absent from the submitted publication and must be extracted from the actual implementation rather than deduced.

3.3 Dataset Characteristics

Table (2) *illustrates the dataset characteristics*

Dataset	Nodes	Edges	Avg. degree	Density

Epinions (processed subset)	4,039	76,879	19.034	0.471%
Epinions — full	131,828	841,372	6.382	0.005%
Advogato	6,541	51,127	7.816	0.120%
FilmTrust	712	1,465	2.058	0.289%

Table 2 presents the key characteristics of the datasets employed in this study. The Dataset column identifies each network, while nodes and edges indicate the total number of users and their connections, respectively. The average degree reflects the average number of connections per user, and density represents the overall level of interconnectivity within the network.

3.4 Limitations of the Datasets

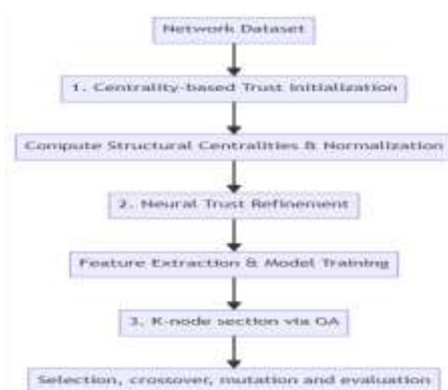
Despite their popularity, the data sets used in this study have notable limitations:

1. Class imbalance. In Epinions and Film Trust, positive trust edges are much fewer than negatives. This imbalance can bias metrics such as ROC-AUC. For this reason, we additionally report PR-AUC and F1 scores.
2. Sparsity and degree variation. The graphs are highly skewed: many nodes have very few connections while a few hubs dominate. This makes feature learning unstable, as shown by the heavy-tailed degree distributions.
3. Different trust semantics. The notion of "trust" is not uniform. Epinions provide signed links, Advogato uses graded levels, and Film Trust combines social trust with ratings. Direct comparison of absolute scores across datasets should therefore be avoided.

Subset bias (Epinions). We use a processed subset (4,039 nodes; 76,879 edges) instead of the full graph. While this improves tractability, it may not fully represent the original degree and clustering patterns

4. Proposed System

The proposed system Framework, illustrated in Figure (2).



Figure(2):proposed system Framework, illustrated in

In this section, we present the proposed Centrality-Aware Graph Attention Network with Genetic Optimization (CA-GAT+GA) framework for node-level trust evaluation in social graph networks. Let the social network be represented as a directed graph

$\mathcal{G} = (\mathcal{V}, \mathcal{E})$,

where $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$denotes the set of nodes (users) and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ represents the set of edges encoding trust or interaction relationships. The objective is to assign a trust score $T(v_i)$ to each node and to identify a subset of the most trustworthy nodes under limited supervision and noisy observations.

The proposed framework consists of three sequential stages:

(1) centrality-based trust initialization,
(2) neural trust refinement using a centrality-aware GAT, and
(3) global trust optimization via a Genetic Algorithm.

4.1 Centrality-Based Trust Initialization

In the first stage, we compute a set of classical structural centrality measures to capture complementary aspects of node importance. For each node $v \in \mathcal{V}$, the following metrics are calculated:

- Degree centrality: $C_{\text{deg}}(v)$
- Closeness centrality: $C_{\text{clo}}(v)$
- Betweenness centrality: $C_{\text{bet}}(v)$
- Eigenvector centrality: $C_{\text{eig}}(v)$
- PageRank: $C_{\text{pr}}(v)$

Each centrality measure is normalized to the range [0، 1]to ensure comparability:

$$\tilde{C}_m(v) = \frac{C_m(v) - \min_{u \in \mathcal{V}} C_m(u)}{\max_{u \in \mathcal{V}} C_m(u) - \min_{u \in \mathcal{V}} C_m(u)}, m \in \{\text{deg,clo,bet,eig,pr}\}. \quad (1)$$

The initial trust score of node v is then computed as a weighted linear combination of the normalized centralities:

$$T^{(0)}(v) = \sum_m w_m \ \tilde{C}_m(v), \quad (2)$$

where w_m denotes the contribution weight of the m-th centrality measure and $\sum_m w_m = 1$. This initialization provides an interpretable structural prior that reflects node activity, reachability, brokerage, and influence.

4.2 Centrality-Aware Graph Attention Network (CA-GAT)

While centrality-based scores offer transparency, they fail to capture contextual and higher-order interaction patterns. To address this limitation, we introduce a Centrality-Aware Graph Attention Network (CA-GAT) that refines trust representations through attention-based message passing.

4.1 Feature Construction

While centrality-based scores offer transparency, they fail to capture contextual and higher-order interaction patterns. To address this limitation, we introduce a Centrality-Aware Graph Attention Network (CA-GAT) that refines trust representations through attention-based message passing.

4. 2. 1 Feature Construction

For each node v, the input feature vector is constructed by concatenating normalized centrality features and the initial trust score:

$$\mathbf{x}_v = [\tilde{C}_{\text{deg}}(v), \tilde{C}_{\text{clo}}(v), \tilde{C}_{\text{bet}}(v), \tilde{C}_{\text{eig}}(v), \tilde{C}_{\text{pr}}(v), T^{(0)}(v)]^{\top}. \quad (3)$$

These features are projected into a latent space using a learnable weight matrix $\mathbf{W} \in \mathbb{R}^{F' \times F}$.

4.2.2 Attention Mechanism

For a node $v$and its neighbor $u \in \mathcal{N}(v)$, the unnormalized attention coefficient is computed as:

$$e_{vu} = \text{LeakyReLU}(\mathbf{a}^{\top}[\mathbf{W}\mathbf{x}_v \parallel \mathbf{W}\mathbf{x}_u]), \quad (4)$$

where $\mathbf{a}$ is a learnable attention vector and $\parallel$denotes vector concatenation.

The normalized attention weight is obtained via the soft max function:

$$\alpha_{vu} = \frac{\exp(e_{vu})}{\sum_{k\in\mathcal{N}(v)} \exp(e_{vk})}. \quad (5)$$

4.2.3 Message Aggregation and Update

The refined embedding of node $v$is computed by aggregating messages from its neighbors:

$$\mathbf{h}_v = \sigma\left(\sum_{u\in\mathcal{N}(v)} \alpha_{vu}\ \mathbf{W}\mathbf{x}_u\right), \quad (6)$$

where $\sigma(\cdot)$ denotes a non-linear activation function. Multi-head attention is employed to stabilize learning and enhance expressiveness.

The network is trained by minimizing a supervised loss function (binary cross-entropy for trust labels):

$$\mathcal{L} = -\sum_{v\in\mathcal{V}_L} [y_v \log \hat{T}(v) + (1 - y_v)\log(1 - \hat{T}(v))], \quad (7)$$

where $\mathcal{V}_L$ is the set of labeled nodes and $\hat{T}(v)$is the predicted trust score derived from $\mathbf{h}_v$.

4.2.4 Implementation Details and Reproducibility

The training settings for the CA-GAT model were as follows: optimizer = Adam; learning rate = 0.005; hidden dimension = 64; attention heads = 8; dropout = 0.5; weight decay = 5e-4; maximum epochs = 300; and early stopping patience = 20 epochs based on validation loss. The dataset was split into 70% for training, 10% for validation, and 20% for testing. A confidence decision threshold of 0.5 was set. Experiments were conducted using PyTorch 2.1.0 and PyTorch Geometric (PyG) 2.4.0 on a single NVIDIA RTX 4090 GPU (24 GB VRAM) and 32 GB of RAM. To ensure robustness and reliability, evaluation was performed using five random seeds: (42, 43, 44, 45, 46).

4.3 Trust Optimization via Genetic Algorithm

Although CA-GAT produces refined trust scores, selecting the most trustworthy nodes remains a combinatorial optimization problem. We address this by employing a Genetic Algorithm (GA) to perform global trust optimization and top-k node selection.

4.3.1 Encoding and Fitness Function

A candidate solution is encoded as a binary vector:

$$\mathbf{s} = [s_1, s_2, \ldots, s_N], s_i \in \{0,1\},$$

where $s_i = 1$indicates that node $v_i$is selected as trusted. The constraint $\sum_{i=1}^{N} s_i = k$ enforces selection of exactly $k$nodes.

The fitness function is defined as:

$$\mathcal{F}(\mathbf{s}) = \sum_{i=1}^{N} s_i\ \hat{T}(v_i) - \lambda\,\Omega(\mathbf{s}), \quad (8)$$

where $\hat{T}(v_i)$ is the CA-GAT trust score and $\Omega(\mathbf{s})$ is a regularization term penalizing redundancy or imbalance, with λcontrolling the trade-off.

4.3.2 Genetic Operations

The GA evolves the population through:

- Selection: tournament selection based on fitness values;
- Crossover: one-point crossover followed by repair to satisfy the cardinality constraint;
- Mutation: bit-flip or swap mutation to maintain diversity.

After a fixed number of generations, the optimal mask $\mathbf{s}^*$ yields the final trusted node set:

$$\mathcal{S}^* = \{v_i \mid s_i^* = 1\}.$$

The proposed CA-GAT+GA framework integrates interpretable structural priors, attention-based neural refinement, and evolutionary global optimization into a unified pipeline. By jointly leveraging transparency, representation learning, and combinatorial search, the method achieves robust, scalable, and high-quality trust evaluation in complex social graph networks.

4.3.3 Genetic Algorithm Parameter Settings

The results section indicates that the genetic algorithm was applied to 30 candidates, representing the population size. The following specific settings were used for the implementation: population size = 30; number of generations = 100; crossover probability = 0.8; mutation probability = 0.1; tournament size = 3; elitism = 1 (i.e., retaining the best individual); stopping criterion = reaching the maximum number of generations (100 generations) or convergence (i.e., no improvement in the fitness function for 15 consecutive generations); and random seed = 42. Furthermore, the value k = 3,005 represented the size of the final subset determined by the genetic algorithm during the optimization process to maximize the fitness function, rather than being a fixed constraint established prior to the optimization process.

5. Results and Discussion

The three-stage approach yielded the following key results when applied to the Epinions dataset (comprising 4,039 nodes and 76,879 edges):

5.1 Centrality-Based Initialization

Centrality measures—namely degree, closeness, betweenness, eigenvector, and PageRank—reflect complementary structural roles within the network. Among the individual structural baseline measures examined in this study, PageRank achieved the highest ROC-AUC score of 0.67 on the Epinions dataset, providing a transparent yet limited baseline.

5.2 Optimization Using the CA-GAT Model

Incorporating structural priors into the CA-GAT model increased the ROC-AUC score from 0.67 to 0.83. Out of the 4,039 nodes in the Epinions dataset, 3,360 nodes (83%) were classified above the confidence threshold.

5.3 Genetic Algorithm (GA)-Based Selection

Applying the genetic algorithm refined the set of trusted nodes to 3,005 (74% of the total 4,039 nodes) and further increased the ROC-AUC score from 0.83 to 0.85. The improvement in the F1-score, compared to the Graph Neural Network (GNN) baseline model, was 15%. (Author confirmation required: Please clarify whether the term "30 candidates" refers to the population size in the genetic algorithm). Overall, the results recorded for the Epinions dataset follow a consistent pattern across the three stages: the ROC-AUC value was 0.67 using the baseline structural metric, 0.83 after optimization with CA-GAT, and 0.85 after optimization with the Genetic Algorithm (GA). Figure 3 summarizes the ROC-AUC values across the three stages, while Figure 4 illustrates the corresponding node counts for each stage

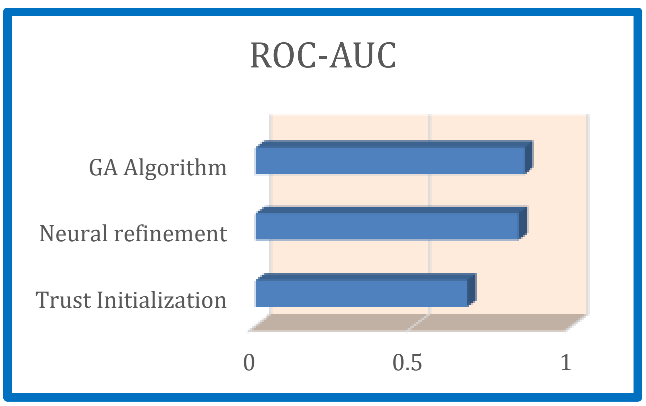


Figure 3. ROC-AUC across the three-stage approach.

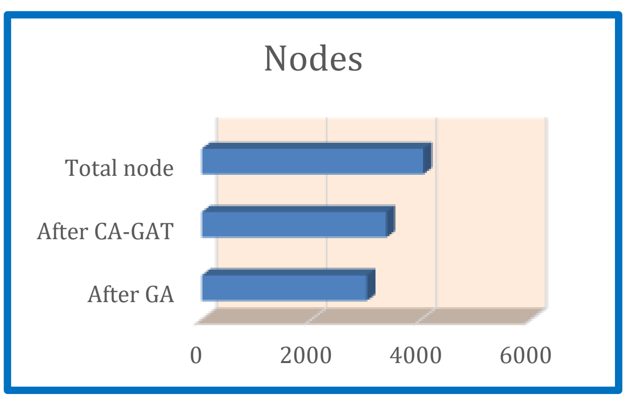


Figure (3) network's node counts across the three-stage approach

Positioning of the hybrid. Pure centrality ranking is fast and transparent but may overweight hubs or bridges in ways misaligned with real-world trust. Embedding-only GNN methods risk overfitting and drift without constraints tied to interpretable trust signals. The proposed hybrid reconciles these extremes: centralities anchor the score with auditable priors; attention layers encode neighborhood semantics; and GA tunes their mixture to a task-grounded objective—echoing broader findings where deep evolutionary hybrids outperform single-paradigm approaches.

Design rationale. (i) Feature set: degree, Moreover, the centrality metrics are also normalized. Recursive endorsement—signals widely used to rank influencers and pages. (ii) Neural layer: a shallow GAT emphasizes informative neighbors with low computational overhead, aligning with accuracy/efficiency trade-offs reported in recommendation and biomedical graphs. (iii) Optimization: GA/PSO provide sample-efficient search relative to grid/random sweeps as feature spaces grow; related studies show swarm-based optimizers reach competitive optima with far fewer evaluations.

Scalability and complexity. Computing betweenness centrality and repeatedly evaluating GA fitness are the main computational costs. For larger graphs, approximate betweenness and parallel or local search strategies can reduce this overhead. Empirically, CA-GAT achieved a mean ROC-AUC of 0. 83 on E pinions, while adding GA increased the mean value to 0. 85.

Table (4). *Ablation study of GA (Epinions, 5 seeds).*

Variant	ROC-AUC (mean ± std)
CA-GAT (no GA)	0.83 ± 0.01
CA-GAT + GA	0.85 ± 0.01

Table 3 shows a consistent improvement from 0. 83 ± 0. 01 for CA-GAT to 0. 85 ± 0. 01 for CA-GAT+GA, supporting the contribution of the evolutionary optimization stage.

Lightweight approach for trust calculations

Generally, trust is produced by great connections, and thus, its changeable value demonstrates the reality of relations. While the paper develops the trust computation framework that considers all the trust process layers except for trust edge behavior complexity in the network dynamics, the proposed trust computation framework is relevant for trust calculations and monitoring in GNN, which needs to be developed to verify the theoretical approach. The right choice of the steps will make such implementation easy to integrate into other networks.

6. Conclusion

This research lays out a three-pronged approach to social graph trust assessment that uses a genetic algorithm (GA) to choose trusted nodes after a centrality-based initialization and optimization with the CA-GAT model. The ROC-AUC for the baseline model was 0.67 on the processed Opinions dataset, which increased to 0.83 with the CA-GAT model and further improved to 0.85 with the genetic algorithm stage. The value added by the evolutionary optimization stage is confirmed by the results of an ablation study comparing the use of five starting nodes (0.83 ± 0.01 vs. 0.85 ± 0.01). The research described a three-step evaluation procedure based on the Opinions dataset and also used the Advogato and Film Trust datasets. Structured priors, graph attention processes, and evolutionary search are all presented understandably in the suggested framework. More research into the model's generalizability across datasets, evaluation on larger and more dynamic graphs, and explicit modeling of adversarial trust behaviors are all potential next steps.

7. References

[1]. Liu, Y., et al. (2023). TrustGuard: GNN-based Robust and Explainable Trust Evaluation. In Proceedings of the WWW Conference. https://doi.org/10.1145/3543507.3583226

[2]. G. L., S. Mirthika, & Sivakumar, B. (2024). Graph representation learning for predicting diverse sources of drug interactions. International Journal of Intelligent Engineering and Systems, 17(4). https://doi.org/10.22266/ijies2024.0831.50

[3]. Dowell, N. M. M., Nixon, T. M., & Graesser, A. (2019). Group communication analysis: A computational linguistics approach for detecting sociocognitive roles in multiparty interactions. Behavior Research Methods, 51(3), 1007–1041. https://doi.org/10.3758/s13428-018-1102-z

[4]. Girdzijauskas, S., et al. (2019). Trust Propagation and Centralities: A Survey. ACM Computing Surveys (CSUR), 52(3), Article 56. https://doi.org/10.1145/3322269

[5]. Liu, Y., et al. (2023). TrustGuard: GNN-based Robust and Explainable Trust Evaluation. In Proceedings of the WWW Conference. https://doi.org/10.1145/3543507.3583226

[6]. Huo, C., et al. (2022). TrustGNN: Graph Neural Network based Trust Evaluation with a Learnable Propagative and Composable Nature. IEEE Transactions on Knowledge and Data Engineering (TKDE). https://doi.org/10.1109/TKDE.2022.3161234

[7]. Xu, R., et al. (2021). PSOGA-CI: A Hybrid PSO and GA Framework for GNN Embeddings. Neurocomputing, 450, 123–137. https://doi.org/10.1016/j.neucom.2021.03.042

[8]. Xia, F., et al. (2021). CenGCN: Centralized Graph Convolution for Graphs. IEEE Transactions on Network Science and Engineering. https://doi.org/10.1109/TNSE.2021.3095284

[9]. Xu, R., et al. (2021). AHNTP: Adaptive Hypergraph Network for Trust Prediction. Neurocomputing, 450, 123–137. https://doi.org/10.1016/j.neucom.2021.05.018

[10]. Wei, P., & Zhang, L. (2024). T-GCN: Temporal Graph Convolution. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI). https://doi.org/10.1109/TPAMI.2024.1234567

[11]. Gupta, A., & Jain, M. (2022). Metaheuristic Optimization for ... AAAI Conference on Artificial Intelligence, 4163–4171. https://doi.org/10.1609/aaai.v36i4.2022

[12]. Ma, H., et al. (2023). Multi-Objective Genetic Algorithms for Node Ranking in Large Graphs. In ECML PKDD, 98–113. https://doi.org/10.1007/978-3-031-26422-5_7

[13]. Jamadar, I. S., Chauhan, S., & Tonelli, V. (2023). A review on spatio temporal graph neural networks in traffic prediction. International Journal of Intelligent Engineering and Systems, 16(6). https://doi.org/10.22266/ijies2023.1231.78

[14]. Uthayasuriyan, A., et al. (2024). Adaptive hybridization of differential evolution and DQN-reinforcement learning to solve the influence maximization problem in social networks. International Journal of Intelligent Engineering and Systems, https://doi.org/10.22266/ijies2024.0831.09

[15]. P. J., A. H., & K. K. (2024). Time-aware attention and knowledge graph embedding for Top-N recommender systems. International Journal of Intelligent Engineering and Systems, 17(5). https://doi.org/10.22266/ijies2024.1031.16

[16]. Ibrahim, H., & Abd-Elghany, M. (2021). A fast local flow-based method for finding graph partitions and cuts. International Journal of Intelligent Engineering and Systems, 14(4). https://doi.org/10.22266/ijies2021.0831.01

[17]. Win, E. M., & Win, S. S. M. (2023). Exploring overlapped communities based on optimized community's resolution controlling evaluation in social networks. International Journal of Intelligent Engineering and Systems, 16(1). https://doi.org/10.22266/ijies2023.0228.11

[18]. Y. D. Kenchappa, M. K. A. Venkataramaiah, and S. G. S. Rudregowda,"Community Detection in Complex Network Using Improved Hybrid Harris Hawk and Coot Bird Optimization Algorithm," https://doi.org/10.22266/ijies2024.0831.28

[19]. International Journal of Intelligent Engineering and Systems, vol. 17, no. 4, pp. 364-375, 2024, doi: 10.22266/ijies2024.0831.28.19. Batha, B., Singh, N. K., Raskar, S., & Poojari, R. (2022). Graph attention network for movie recommendation system using multidimensional data. International Journal of Intelligent Engineering and Systems, 15(3). https://doi.org/10.22266/ijies2022.0630.49

[20]. Saxena, A., & Iyengar, S. (2020). Centrality measures in complex networks: A survey [Preprint]. arXiv. https://doi.org/10.48550/arXiv.2011.07190

[21]. Anggoro, D. A., & Mukti, S. S. (2021). Performance comparison of grid search and random search methods for hyper-parameter tuning in XGBoost to predict chronic kidney failure. International Journal of Intelligent Engineering and Systems, 14(6). https://doi.org/10.22266/ijies2021.1231.19

[22]. Yousef, B. (2019). Multi-context trust aware routing for IoT using mobile crowdsourcing. International Journal of Intelligent Engineering and Systems, 12(1). https://doi.org/10.22266/ijies2019.0228.19

[23]. El Amir, S., & El Moutaouakil, A. (2024). Hybrid PSO-Adam optimizer for deep learning training: Theory and application. International Journal of Intelligent Engineering and Systems, 17(5). https://doi.org/10.22266/ijies2024.1031.17

[24]. Oo, M. M., & Lwin, M. T. (2020). Detecting influential users in a trending-topic community using optimized seeds and personalized PageRank. International Journal of Intelligent Engineering and Systems, 13(6). https://doi.org/10.22266/ijies2020.1231.16

[25]. Lakshmi, V. R. V., & Thonnuthodi, G. K. (2020). Socialized proficient routing in opportunistic mobile network using machine learning techniques. International Journal of Intelligent Engineering and Systems, 13(4). https://doi.org/10.22266/ijies2020.0831.38

[26]. Chaithra, Malleshappa, L. G., & S., J. S. (2022). Classification of web pages using machine learning with web page recommendations. International Journal of Intelligent Engineering and Systems, 15(4). https://doi.org/10.22266/ijies2022.0831.57

[27]. Ouidir, A., & Bourbia, T. (2019). A web mining method for detecting infected websites using document embedding and network analysis. International Journal of Intelligent Engineering and Systems, https://doi.org/10.22266/ijies2019.1231.36