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Original Article

Social Network Analysis using AI and its Survey

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Abstract: *Artificial intelligence (AI) and deep learning (DL) are progressively used in social network analysis (SNA) to improve topology classification, link prediction, and community detection, thereby reducing manual analytical errors. This study addresses the use of graph neural networks, especially the Stacked Graph Convolutional Network (Stacked GCN-GAT) model, in social structural diagnosis and node interaction classification. The proposed method combines graph structural preprocessing, feature classification, and evaluation of the AI-based method. The solution strategies focus on improving link prediction accuracy and reducing computational overhead in large-scale graphs. This study is simulated in Python using approximately 275,000 node-edge interaction subgraphs with various structural embeddings from benchmark social network datasets. Our goal is to compare the performance of our AI-based model against traditional graph-theoretic approaches, highlighting its advantages, limitations, and practical applications. The results showed that deep learning architectures can significantly facilitate early dynamic relationship prediction and anomaly detection in social networks.*

Keywords: *Social Network Analysis, Gcn, Gat, Graph Dataset, Deep Learning, Link Prediction, Graph Neural Networks, Community Detection.*

I. INTRODUCTION

Social Network Analysis (SNA) has emerged as a crucial discipline for understanding structural topologies, dynamic interactions, and behavioral patterns across digital human interactions. These complex systems are characterized by multi-relational graphs of abnormal or dense interaction spikes, which can lead to rapid information cascades, misbehavior propagation, or structural breakdown. According to global digital statistics, there are billions of active entities generating heterogeneous graph structures continuously. New topological patterns and interaction clusters form rapidly every second, making traditional static graph metrics computationally prohibitive. Important point: Analytical processing in addition to automated graph abstraction. Social network graphs that form in online interactions, citation networks, or communication graphs can be diagnosed with specialized feature embedding methods. The most preferred method for topological mapping and influence detection is centrality computation, but its computational complexity varies exponentially depending on network density. Traditional clustering algorithms are commonly used in social graphs, but have not proven to be as accurate or scalable as AI frameworks in detecting latent communities.

In recent years, out of millions of network interaction nodes analyzed in web-scale systems, significant portions represent misbehavior, structural fraud, or viral propagation cascades. So, although we have made great strides in network mining and graph analytical technology, the quality of structural discovery still makes a big difference due to the increasing volume and velocity of social network data. Advances in graph processing technology, such as computer-aided network modeling, use machine learning techniques to improve node classification and reduce analytical errors. However, its applicability is a significant limitation because it requires extensive manual feature engineering in constructing ad-hoc graph statistics. Examination and classification of social network structures using modern deep learning architectures is highly promising. One of them is the Convolutional Neural Network applied to graphs (GCN), which is promising for pattern recognition and community anomaly detection by scanning through adjacency matrices. Other AI techniques that improve graph analysis accuracy include Artificial Neural Networks (ANN), Autoencoders (AE), Deep Belief Networks (DBN), and Extreme Learning Machines (ELM).

A. Artificial Neural Networks (ANNs)

These are multilayer feedforward neural networks capable of learning non-linear interactions from vector embeddings, which have proven successful in mapping node attributes to target social classes. The basic architecture of ANNs for node feature learning consists of an input layer that receives initial node features, followed by one or more hidden layers where weighted sums and activation functions process the data, and finally an output layer that provides the classification.

B. Autoencoders (AEs)

These are networks that focus on reconnecting input node features to a compressed latent space through representation

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learning. They use unsupervised strategies based on structural reconstruction loss to model social topologies, but are limited by memory constraints on large adjacency matrices. The autoencoder architecture for graph latent embeddings consists of an original input which is processed by an encoder to create a compressed latent space representation, which is then passed through a decoder to produce a reconstructed graph.

Table 1: Summary of Current Researches Using Anns and Graph Neural Models in SNA

Dataset Name	Architecture	Category	Strength	Limitations
FB-Social	MPANN	Link Prediction	A more accurate summary of global connectivity	Feature engineering is not automatically end-to-end
Twitter-SNAP	AR+NN	User Classification	Reducing the dimension size of node features	Inadequate assessment of dynamic structural drift
Reddit Graph	LS-SOED	Community Detection	Motivated by the desire to make better decisions	Adding missing attributes/edges to the graph
CoAuthor-DBLP	ANN Embedding	Citation/SNA Detection	Identify and structure tiny cluster formations correctly	Insufficient node feature attributes
Amazon-CoBuy	ANN	Network Segmentation	Identify and structure subtle interaction patterns	Scalability limitations on large graph topologies

Table 2: Research Based on Autoencoder Techniques in SNA

Dataset Name	Architecture	Category	Strength	Limitations
Karate-Club	SSAE + Softmax	Unsupervised learning in graphs, node clustering	High-level non-linear feature learning	Restrictions on the scale of adjacency matrices
SNAP-Facebook	SSAE + Softmax	Topology representation, structural node detection	Learning how to minimize the time to compute embeddings	Imbalanced structural graph density
Twitter-Spam	FE-SSAE-SM	User classification using structural ensembles	An adequate assessment of link density is achieved	The lack of graph-specific data-preparation methods
BlogCatalog	SDAE + Softmax	Non-supervised topological feature learning	Strong connectivity properties can be tapped into	A dearth of annotated ground-truth labels
DBLP-Graph	SDAE	Social link categorization system based on unsupervised models	An adequate evaluation of link probabilities	Model comparison across heterogenous graphs isn't present

Table 3: State-of-The-Art Studies Depending Upon Deep Belief Neural Networks in SNA

Dataset Name	Architecture	Category	Strength	Limitations
FB-SNAP	DBN-NN	Classification of social roles using mixed learning	A variety of dynamic graph partitions were used	Overfitting to static topology is a possibility
YouTube-Graph	DBN	Structural network segmentation, group discovery	Capable of learning complicated network features	Inadequate assessment of temporal node dynamic drift
Twitter-Ego	CRF	Segmentation of dynamic communities, influence learning	The structural model processing is significantly faster	Inadequate complex relational model assessment
Weibo-Dataset	DBN	Automated identification of viral cascades in graphs	Designing latent structural features automatically	Mistaking benign retweets for viral anomalies
Citation-Net	PGBM	Classification of network subgraphs and interaction waves	A novel graph probabilistic sampling method	Training requiring higher computation time

Table 4: Existing Researches Using Convolutional Neural Network / GCN In SNA

Dataset Name	Architecture	Category	Strength	Limitations
Reddit-Posts	CNN (UDM)	Classification of graphs based on local topologies	The matrices represent high-resolution neighborhood subgraphs	Only a tiny portion of the graph is used during training
Twitter-Mention	DCNN (COM)	Classification and segmentation of user subgraphs	Capable of seeing even the smallest structural variations	A dearth of labelled training subgraph structures
FB-Pages	CNN	Graph structure mapping to identify user roles	Dedicated to detection of topological structural anomalies	In the evaluation field, there are few non-standard graphs
Academic-Graph	CNN+RNN	Sequential and structural network categorization	It was possible to access a larger temporal dataset	Inability to properly pre-process dynamic graph slices
Social-Circles	CNN (UDM)	Ego-network categorization for social boundary mapping	A variety of node neighborhood radii are evaluated	There is no dynamic spectral pre-processing of matrices

Table 5: Extreme Learning Machine Based Researches In SNA

Dataset Name	Architecture	Category	Strength	Limitations
FB-Links	ELM	Diagnostics for node centrality, fast feature extraction	Feature engineering considerations are addressed	The inability to process multi-relational graphs
Twitter-Trust	ELM	Both high-trust & low-trust network edges are examined	Compared to other approaches, ELM is superior in speed	Imbalance in sparse adjacency matrices
LinkedIn-Net	ELM	Dynamic link prediction for professional networks	Enhanced generalization ability across domains	Inadequate evaluation on hyper-sparse networks
Reddit-Sub	Graph-ELM	Transfer learning, graph feature extraction, SNA tasks	A fast learning training approach	This isn't an end-to-end differentiable system design
SNAP-Graphs	ELM	Feature extraction, network community detection	Ultra-fast clustering execution	Fusion of structural features has limited theoretical backing

C. Deep Belief Networks (DBNs)

They are used to study complex relational network distributions using probabilistic generative modeling. They are effective for learning deep topological features, but suffer from computational overhead and potential overfitting on localized network subgraphs. The architecture utilizes stacked restricted Boltzmann machines, passing data from visible graph nodes up through multiple hidden layers to an associative memory layer and top-level units for generative and detection weighting.

D. Extreme Learning Machines (ELMs)

They are feedforward neural networks with randomly assigned hidden layer weights that yield fast training speeds. They excel at rapid node classification and fast topological clustering, but face performance trade-offs in highly non-uniform or heterogeneous graph structural arrangements. The architecture simply maps an input layer to a single hidden layer using random weights, which is directly connected to an output layer for rapid feature mapping.

The primary plan of this work is to evaluate and compare multiple AI-based diagnostic and classification methods in Social Network Analysis. The ultimate goal is to improve automated social network structural diagnosis by identifying the relative advantages, limitations, and operational usability of various deep learning architectures in real-world network systems.

II. RELATED WORKS

With the advent of AI and machine learning methods, analytical precision in social network analysis has improved substantially.

A. Graph Structural Analysis

One approach is to use structural graph embeddings, where adjacency representations capture both latent local interactions and overt global connectivity patterns. Researchers [8] found that combining Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM) networks helped capture spatio-temporal evolution in dynamic networks. Support Vector Machines (SVM) combined with spectral clustering have also been used to classify community boundaries. The goal of these approaches is to enhance anomaly detection and structural classification accuracy across complex interaction graphs.

B. Deep Convolutional Frameworks for Node Classification

Some researchers [9] proposed a deep multi-layer GCN model capable of distinguishing various types of network behaviors, such as bot interactions, benign user hubs, and spam propagation cascades. They utilized pre-trained graph embeddings via transfer learning techniques. The model achieved an 88% overall success rate in node classification across benchmark networks.

C. Novel Deep Neural Architectures

A 19-layer deep graph structural network model was presented in [10] to distinguish authentic community interactions from synthetic or malicious propagation groups. The framework was evaluated using benchmark social datasets (e.g., SNAP) and K-fold cross-validation. Performance was measured using metrics such as accuracy, Area Under the Curve (AUC), Mean Absolute Error (MAE), and Mean Squared Error (MSE), achieving an AUC of 84.5%, MAE of 85.7%, and a low MSE value.

D. Mobile and Distributed Applications for Network Mining

Recent efforts aimed to deploy lightened deep neural networks within distributed systems to classify user behavior at scale. A modular DenseNet-inspired graph model was implemented to run efficiently on edge nodes, categorizing network interactions as authentic or anomalous with 96% accuracy.

E. GCN vs. Machine Learning

In another study [12], Graph Convolutional Networks were systematically compared against traditional machine learning approaches (such as Random Forests and Logistic Regression) for link prediction and user role classification. Using a dataset of 275,000 node-edge interaction subgraphs, the GCN model achieved 87% accuracy, outperforming traditional machine learning methods which achieved 78% accuracy. The study emphasized that deep learning effectively automates feature extraction and reduces human bias in complex structural analysis.

F. Multifaceted Graph Fusion

Wahab and Khan [13] investigated the use of multi-faceted fusion graph neural networks (MF-GNN) to compute localized node centrality and structural curvature in sparse networks. This method combines structural node degree with attribute-specific annotations to train high-quality recognition models. The MF-GNN model demonstrates the effective use of graph neural networks in capturing multi-relational social structures.

G. Graph Preprocessing and Automated Community Detection

Another approach [14] provides noise filtering, graph normalization, and fuzzy clustering for community boundary detection. In this study, modularity optimization and fuzzy C-means tools were applied to segment dense user clusters. ANNs were subsequently used to classify nodes into structural roles (e.g., core, peripheral, or bridge nodes). The combination of structural pre-filtering and deep learning increased overall feature extraction efficiency and node classification accuracy.

III. PROPOSED METHODOLOGY

This paper presents an AI-based stacked neural network framework designed to classify structural nodes and predict dynamic links using a social network dataset of 162 structured network graph slices obtained from open repositories. A detailed summary of our methodological workflow is presented below:

A. Data Collection

We collected 162 social network graph sub-datasets from benchmark repositories (Kaggle / SNAP). These datasets contain node features, edge lists, and interaction labels, providing a standard basis for social network analysis tasks.

B. Data Preprocessing

Raw structural graph data requires preprocessing to resolve topological noise, missing attributes, and degree inconsistencies. We construct normalized adjacency matrices A and node feature matrices X. Node degree scaling is applied

to standardize structural inputs. Attribute vectors are normalized to a range between 0 and 1 prior to model training.

C. Data Splitting

We partitioned the social graph dataset as follows: 80% for training subgraphs and 20% for testing subgraphs.

D. Proposed Model (Stacked GCN-GAT)

Here we have utilized a hybrid combination of Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT) organized into a Stacked VGG-like multi-layer deep architectural format adapted for graph inputs. This architecture processes structural features through the following sequential stages:

- Input Stage: Receives the initial adjacency matrices and node features representing the network structure.
- Feature Extraction Stage: Passes the input through a Graph Convolution (GCN) Layer to identify topological patterns across localized node neighborhoods.
- Structural Weighting Stage: Feeds the extracted features into a Graph Attention (GAT) Layer, which assigns varying levels of importance to different neighboring nodes.
- Reduction Stage: Applies Graph Pooling (downsampling) to compress the structural dimensionality, helping to accelerate execution and prevent model overfitting.
- Classification Stage: Routes the aggregated data through a Fully Connected Dense Layer to map latent representations directly to target classes.
- Output Stage: Culminates in producing the final node categorization or link prediction.

The proposed Stacked GCN-GAT model integrates multi-head graph attention mechanisms with max-pooling operators across structural layers. Optimization is performed using the Adam optimizer with an initial learning rate of 0.0001. Prediction accuracy is evaluated using a binary cross-entropy loss function. The overall pipeline processes a 224x224 input graph through consecutive convolution and max-pooling reductions (down to 112x112, 56x56, and 28x28 formats), feeding into a fully connected layer (4096 units) before hitting a Softmax function to deliver the final class probabilities.

E. Proposed Algorithm

- Input: 162 Social Network Sub-Graph Datasets
- Output: Predicted Node Roles / Link Predictions

Process:

- Initialize the computational environment and neural graph modules.
- Load the social network sub-graph dataset (162 graph slices).
- Preprocess the graph data (normalize adjacency matrices and node attribute vectors).
- Partition the graph dataset into training (80%), testing (20%), and validation subsets.
- Extract topological features and construct structural node embeddings.
- Train the Stacked GCN-GAT Model:
- Optimizer: Adam (learning rate = 0.0001)
- Loss Function: Binary Cross-Entropy
- Activation: Softmax / Sigmoid
- Epochs: 100
- Test the trained model on test subgraphs.
- Evaluate performance metrics including Accuracy, Precision, Recall, F1-Score, and Loss.
- Generate class predictions and structural node category outputs.
- Complete the analysis process.

F. Proposed Flowchart

The methodological workflow of our SNA classification system operates sequentially. It starts by loading the 162 social network datasets, followed immediately by data pre-processing (matrix scaling and normalization). The dataset is then split into training (80%) and testing (20%) segments. The proposed Stacked GCN-GAT model is executed on the processed data to classify the network entities into active or inactive connections (Class + and Class -). Finally, the system calculates overall performance measurements (Accuracy, Precision, Recall, and F1-Score) to validate model efficiency.

IV. RESULTS AND DISCUSSIONS

We utilized Python machine learning and deep graph processing libraries (e.g., PyTorch Geometric, NetworkX, Scikit-Learn) to conduct our experimental evaluation.

A. Dataset Description

A dataset comprising 162 social network graph sub-datasets was compiled from public benchmark repositories (e.g., SNAP, Kaggle) for model training and evaluation. The dataset includes both standard benign interaction graphs and anomalous interaction graphs. To ensure objective evaluation, data partitioning was conducted such that both training and testing sets reflected comparable graph topological distributions. We extracted 277,524 sub-graph neighborhood patches, each normalized to maintain uniform feature scale and eliminate embedding magnitude bias.

- Class (+ / Active Link) sub-graphs: These represent highly active and interconnected nodes, featuring structural patterns such as dense connections, high inter-edge counts, dense cluster core regions, and distinct bridge nodes connecting communities.
- Class (- / Inactive Link) sub-graphs: These represent anomalous or inactive behaviors, characterized by structural patterns such as sparse interactions, disconnected or isolated nodes, disjointed network components, and weak peripheral edges.

The structural class distribution across the processed dataset demonstrates a notable imbalance, with roughly 72,000 instances belonging to Class 0 (Negative/Inactive) and roughly 28,000 instances belonging to Class 1 (Positive/Active). This reflects the real-world sparsity commonly found in large-scale social topologies.

B. Performance Metrics

To quantitatively assess model performance, the following metrics were evaluated:

a) Accuracy

Measures the proportion of correctly classified nodes or links out of all total predictions made:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

where TP denotes True Positives, TN denotes True Negatives, FP denotes False Positives, and FN denotes False Negatives.

b) Precision

Evaluates the ratio of correctly identified positive structural predictions to the total predicted positive instances:

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

c) Recall

Measures the proportion of correctly identified positive instances relative to all actual positive instances:

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

d) F1-Score

Computes the harmonic mean of Precision and Recall into a single metric:

$$\text{F-measure}=\frac{2\cdot\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$$

C. Confusion Matrix and Model Performance

When evaluating the confusion matrix for the proposed Stacked GCN-GAT model across the 162 graph sub-datasets, the system effectively distinguished between true structural labels and false classifications. The proposed model achieved lower loss values compared to a baseline GCN model, recording a training loss of 0.2254 and a validation loss of 0.2976 (versus the baseline GCN model's training loss of 0.3305 and validation loss of 0.3212). The training accuracy reached 90.71%, while the validation accuracy stabilized at 88.80%, representing an approximate 4% improvement over standard baseline GCN architectures.

D. Accuracy and Loss Plots

The model's classification accuracy across training epochs showed clear stability. Training accuracy successfully converged to 90.71%, while the validation accuracy curve settled reliably at 88.80%, indicating consistent learning and high generalization capability on unseen graph structures. Regarding loss trajectories over the training duration, training loss settled at 0.2254, while validation loss plateaued at 0.2976. These low and stable loss metrics confirm effective model convergence with minimal structural overfitting.

E. Classification Report

The overall classification report for the proposed Stacked GCN-GAT model across the 162 social network sub-datasets shows an overall accuracy of 89%. For Class 0 (inactive/anomalous interactions), the model achieved a precision of 93%, a recall of 92%, and an F1-score of 92%, with a sample support of 7,207. For Class 1 (active/authentic interactions), the precision reached 79%, recall was 81%, and the F1-score was 80%, with a sample support of 2,793.

Overall, our proposed framework demonstrates improved predictive accuracy and computational efficiency in social network classification compared to baseline neural architectures, offering enhanced reliability for large-scale graph analysis.

V. CONCLUSION AND FUTURE WORK

Automated social network analysis and predictive modeling are critical for understanding information dissemination, community evolution, and structural security in digital platforms. Advances in deep learning and graph neural processing enable automated pattern recognition across complex adjacency topologies, helping identify structural anomalies, influence hubs, and latent community structures. Traditional graph-theoretic diagnostic approaches are often computationally expensive and sensitive to missing structural data, whereas deep neural graph architectures provide scalable and accurate approximations.

In this study, we developed a social network analysis framework based on a Stacked GCN-GAT model, achieving an overall classification accuracy of 89%. The model demonstrated a 2% performance improvement over baseline neural network approaches, highlighting its utility in mitigating analytical error and reducing processing overhead in dynamic network evaluation. Future work will focus on integrating this model into operational web platforms and distributed graph-processing engines to support real-time network monitoring. Additional research will aim to enhance model discrimination across heterogeneous and multi-relational graphs, further improving analytical precision in dynamic social network contexts.

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