Machine Learning Course Project Report

EEG-Based Emotion Recognition: A Deep Learning Approach Integrating Contrastive Learning, GANs, GNNs and Graph Attention Networks

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CERTIFICATE

This is to certify that the Course project Work Report entitled **"EEG-Based Emotion Recognition: A Deep Learning Approach Integrating Contrastive Learning, GANs, GNNs and GAT"** is submitted by the group mentioned below -

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EEG-Based Emotion Recognition: A Deep Learning Approach Integrating Contrastive Learning, GANs, GNNs and Graph Attention Networks

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This work was carried out as part of an academic project at the Department of Information Technology, National Institute of Technology Karnataka, Surathkal.

ABSTRACT Emotion recognition through physiological signals has become a key area in affective computing and human–computer interaction. This study focuses on classifying emotional states using EEG signals from the DEAP dataset by leveraging the power of Graph Neural Networks (GNNs). Each EEG channel is treated as a node in a graph, capturing spatial and temporal dependencies through attention-based mechanisms. The data preprocessing includes loading and standardizing multi-subject EEG signals, extracting 32-channel features, and labeling them based on valence and arousal levels. A Graph Attention Network (GAT) is implemented to model inter-channel relationships and learn discriminative representations of emotional patterns. The model is trained and evaluated for both valence and arousal classification, demonstrating the effectiveness of graph-based deep learning in emotion recognition tasks. Experimental results indicate that GATs can efficiently capture the complex correlations among EEG electrodes, leading to improved performance compared to traditional neural models.

INDEX TERMS Contrastive Learning, Graph Adversial Networks (GANs), Graph Neural Networks (GNNs), Graph Attention Network (GAT)

I. INTRODUCTION

EMOTION recognition has emerged as a fundamental problem in Affective Computing, with applications in healthcare, adaptive learning, entertainment, and human–computer interaction. Among various modalities, Electroencephalography (EEG) has proven to be a reliable and direct measure of human emotional and cognitive states due to its high temporal precision and ability to capture neural activity patterns. However, the inherent complexity, noise, and inter-subject variability of EEG signals make emotion recognition a challenging task.

To address these challenges, recent advances in Graph Neural Networks (GNNs) have enabled the modeling of EEG signals as graphs, where nodes correspond to electrodes and edges capture spatial or functional relationships between brain regions. This representation allows for the integration of both spatial connectivity and temporal dynamics in emotion classification. In particular, Graph Attention Networks (GATs) introduce attention mechanisms to dynamically assign importance to neighboring electrodes, improving the network's ability to learn discriminative patterns relevant to emotional states.

In this study, we propose a hybrid framework that combines GNN-based feature learning with Contrastive Learning and Graph Adversarial Networks (GANs) to enhance model generalization and robustness. Contrastive learning is employed to enforce feature similarity among samples of the same emotion class while maximizing separation between distinct emotions, thereby improving latent space structure. Meanwhile, adversarial regularization through GANs helps the GNN model resist overfitting and enhances cross-subject transferability by generating synthetic graph embeddings that mimic real EEG patterns.

The experiments are conducted on the DEAP dataset, a widely used benchmark for EEG-based emotion recognition, focusing on the two key affective dimensions—valence and arousal. The proposed approach demonstrates that the integration of GNNs, GATs, contrastive objectives, and adversarial learning significantly improves the accuracy and stability of emotion classification models, paving the way for more reliable affective computing systems.

II. RELATED WORK

TO position the present research within the existing body of work, this section provides a comprehensive overview of recent advancements in EEG-based emotion recognition. Particular emphasis is placed on graph neural approaches, attention mechanisms, contrastive representation learning, and adversarial generative models that have influenced the design of the proposed framework.

A. GRAPH NEURAL NETWORKS IN EEG EMOTION RECOGNITION

The use of graph-based neural networks to model the spatial and functional relationships between EEG electrodes has grown rapidly. For example, EEG-Based Emotion Recognition Using Regularized Graph Neural Networks (Zhong et al., 2019) propose a Regularized GNN (RGNN) that explicitly encodes biological-topology inspired adjacency among EEG channels, and adds regularisers for cross-subject variation and noisy labels. Another work, A Comprehensive Survey on EEG-Based Emotion Recognition: Graph-Related Methods (2024) provides a systematic overview of graph-related models in EEG emotion recognition, highlighting how adjacency structure, node features, and message-passing schemes are evolving. arXiv More recently, Fusion Graph Representation of EEG for Emotion Recognition (2023) propose fusing multiple relation-graphs (topological, functional, causal) via a graph convolutional network (GCN) to produce richer representations of EEG channels. These works demonstrate that representing EEG channels as nodes in a graph and leveraging their inter-relationships can significantly boost emotion recognition performance over treating channels independently.

B. GRAPH ATTENTION NETWORKS AND ATTENTION-BASED GRAPH MODELS

Beyond standard GCNs, attention-mechanisms on graphs allow models to assign varying importance to neighboring nodes/channels. For instance, DAGAM: Domain Adversarial Graph Attention Model for Subject Independent EEG-Based Emotion Recognition (2022) use a Graph Attention Network (GAT) combined with domain adversarial training to tackle cross-subject generalisation. Another example, EEG-based Emotion Recognition using Graph Convolutional Neural Network with Dual Attention Mechanism (2024) integrate dual-attention (channel electrode attention + frequency band attention) into a GCN framework to more effectively extract discriminative features for emotion recognition. Another example, EEG-based Emotion Recognition using Graph Convolutional Neural Network with Dual Attention Mechanism (2024) integrate dual-attention (channel electrode attention + frequency band attention) into a GCN framework to more effectively extract discriminative features for emotion recognition.

C. CONTRASTIVE LEARNING IN EEG/GRAPH SETTINGS

Contrastive learning—learning representations by pulling similar pairs together and pushing dissimilar apart—has recently been applied in EEG emotion recognition to improve embedding robustness. For example, Emotion recognition of EEG signals based on contrastive learning graph convolutional model (2024) propose the CL-GCN which combines contrastive loss with GCN on EEG data, achieving strong cross-subject generalisation. This suggests that the embedding space structure (beyond simply classification loss) is important, especially given variability across subjects and sessions in EEG. Your inclusion of contrastive learning in your pipeline is therefore well-aligned with current trends.

D. GENERATIVE ADVERSARIAL NETWORKS (GANS) FOR EEG EMOTION RECOGNITION

GANs are primarily applied in this domain for data augmentation and domain adaptation, addressing limited labelled EEG data and cross-subject variability. For instance, EEG Data Augmentation for Emotion Recognition with a Task-Driven GAN (2023) propose a task-driven conditional Wasserstein GAN (CWGAN) to generate artificial EEG feature-maps (differential entropy) to enhance classifier performance. Another work, Improved BCI calibration in multimodal emotion recognition using heterogeneous adversarial transfer learning (2024) uses GANs (conditional, Wasserstein) in a heterogeneous adversarial transfer learning context to reduce calibration effort in emotion recognition across modalities.

III. PROPOSED METHODOLOGY

THIS study introduces a comprehensive framework for EEG-based emotion recognition by integrating self-supervised contrastive learning, adversarial data augmentation, and graph-based neural classification. The methodology progresses through four major stages—EEG preprocessing, feature extraction via contrastive learning, data augmentation through class-conditional GANs, and classification using Graph Neural Networks (GNNs) enhanced with Graph Attention Networks (GATs).

A. EEG DATA PREPROCESSING

The experiments are conducted on the publicly available DEAP dataset, which comprises 32-channel EEG recordings sampled at 128 Hz from 32 participants watching affective video stimuli. Each trial is annotated with self-reported *valence* and *arousal* scores ranging from 1 to 9.

The preprocessing pipeline consists of several key steps:

- **Channel selection:** Only the first 32 EEG channels are retained to maintain a consistent topography across participants.
- **Temporal truncation:** Each recording is trimmed to the first 7680 samples to standardize trial length.
- **Normalization:** Each channel is normalized using z-score normalization to reduce inter-subject variability.
- **Label binarization:** Continuous valence and arousal scores are binarized into ‘‘Low’’ (1–5) and ‘‘High’’ (6–9) using median thresholding.

The resulting dataset is split into 80% for training and 20% for testing, ensuring stratified class balance. Data loading and preprocessing are implemented via a custom `DEAPDataLoader` class that automates reading, labeling, and partitioning.

B. CONTRASTIVE LEARNING FOR REPRESENTATION EXTRACTION

EEG signals are inherently non-stationary and subject to noise. To obtain noise-robust and semantically rich embeddings, we employ a self-supervised contrastive learning (CL) module that learns invariant features without explicit labels.

1) Network Architecture

The CL model comprises two components:

1) **Channel Encoder:** A convolutional feature extractor with three 1D convolutional layers:

$$x^{(l+1)} = \mathrm{ReLU}(\mathrm{BN}(\mathrm{Conv1D}(x^{(l)}))),$$

where each layer progressively increases receptive field size and channel depth (from 32 to 64 and back to 32 filters).

2) **Projection Head:** A two-layer MLP that projects the encoder output into a lower-dimensional latent space ($d = 128$), followed by ℓ_2 normalization to constrain the embeddings on a unit hypersphere.

2) Contrastive Objective

During training, two random augmentations of each EEG trial are generated using:

- additive Gaussian noise ($\sigma = 0.05$),
- random temporal shift (up to 500 samples),
- amplitude scaling ($\times[0.8, 1.2]$), and
- channel dropout ($p = 0.1$).

Given two views x_1 and x_2 of the same trial, the model produces embeddings z_1 and z_2. The NT-Xent loss [**?**] is used:

$$\mathcal{L}_{CL} = -\log \frac{\exp(\mathrm{sim}(z_1, z_2)/\tau)}{\sum_{k=1}^{2N} \mathbf{1}_{[k \neq i]} \exp(\mathrm{sim}(z_1, z_k)/\tau)},$$

where $\mathrm{sim}(a, b)$ is cosine similarity and $\tau = 0.1$ is the temperature. This encourages the model to learn invariant features by maximizing similarity between augmented views of the same trial and minimizing similarity with others.

After training, encoder features from the last convolutional layer are extracted as fixed representations for subsequent GAN and GNN stages.

C. GAN-BASED DATA AUGMENTATION

EEG datasets are often limited and imbalanced across emotion categories. To overcome this, we employ a class-conditional Generative Adversarial Network (GAN) to synthesize realistic EEG-like embeddings, balancing the dataset and improving model generalization.

1) Generator and Discriminator Design

The generator G receives a random noise vector $z \in \mathbb{R}^{256}$ concatenated with a class embedding vector E_y and produces a synthetic EEG feature sequence $\tilde{x} \in \mathbb{R}^{32\times120}$. Its structure consists of three fully connected layers with batch normalization and ReLU activations, ending with a `tanh` layer to bound the output. The discriminator D uses two spectral-normalized 1D convolutional layers followed by adaptive pooling and a fully connected classifier to distinguish between real and synthetic samples.

2) Training Objective

The adversarial learning follows the classical minimax objective:

$$\min_G \max_D \; \mathbb{E}_{x\sim p_{\mathrm{data}}}[\log D(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - D(G(z)))].$$

Each class-specific GAN is trained independently for 150–200 epochs until the generated samples achieve high discriminator confidence. The synthetic embeddings are combined with real samples to form an augmented and balanced training set:

$$\mathcal{D}_{aug} = \mathcal{D}_{real} \cup \mathcal{D}_{synthetic}.$$

D. GRAPH REPRESENTATION OF EEG CHANNELS

After augmentation, each EEG trial is represented as a graph $G = (V, E)$, where each node $v_i \in V$ corresponds to an EEG electrode and edges encode spatial proximity or functional correlation. Node features are the channel embeddings produced by the CL encoder or GAN. The adjacency matrix A is initialized using a Gaussian kernel:

$$A_{ij} = \begin{cases} \exp\left(-\frac{\|p_i - p_j\|^2}{2\theta^2}\right), & \text{if } \|p_i - p_j\| \le \lambda, \\ 0, & \text{otherwise.} \end{cases}$$

Here, p_i and p_j are the 3D electrode coordinates, $\lambda = 5$ controls connectivity radius, and $\theta = 2$ determines decay smoothness. The adjacency matrix is learnable, allowing the model to refine electrode relations during training.

E. GNN–GAT EMOTION CLASSIFIER

The final classification model combines Graph Neural Networks (GNNs) for relational message passing and Graph Attention Networks (GATs) for adaptive weighting of inter-channel dependencies.

1) GNN Message Passing

Given input node features $H^{(0)} = X$, each GNN layer updates node embeddings using:

$$H^{(l+1)} = \sigma\left(AH^{(l)}W^{(l)}\right),$$

where A is the normalized adjacency matrix, $W^{(l)}$ are trainable weights, and $\sigma(\cdot)$ is the ReLU activation. This process aggregates neighborhood information across EEG channels, capturing both spatial and temporal correlations.

2) Graph Attention Mechanism

To enable data-driven edge weighting, a multi-head Graph Attention Network (GAT) layer [?] is applied. Attention coefficients are computed as:

$$\alpha_{ij} = \frac{\exp\left(\mathrm{LeakyReLU}\left(a^T [Wh_i \,||\, Wh_j]\right)\right)}{\sum_{k \in \mathcal{N}(i)} \exp\left(\mathrm{LeakyReLU}\left(a^T [Wh_i \,||\, Wh_k]\right)\right)},$$

where a is the learnable attention vector, and $||$ denotes concatenation. Each node's representation is updated as:

$$h_i' = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} W h_j\right).$$

Multi-head attention (4 heads) improves model stability and representation diversity.

3) Classification Layer

After message passing, node embeddings are aggregated, and the representation of the target electrode (Cz) or averaged embedding is passed through a fully connected layer and a softmax classifier to predict *High* or *Low* valence/arousal states.

F. TRAINING OBJECTIVE AND OPTIMIZATION

The entire network is optimized end-to-end with the composite loss function:

$$\mathcal{L}_{total} = \mathcal{L}_{CE} + \lambda_1 \mathcal{L}_{CL} + \lambda_2 \mathcal{L}_{GAN},$$

where $\mathcal{L}_{CE}$ is the cross-entropy classification loss, $\mathcal{L}_{CL}$ is the contrastive alignment term ensuring feature consistency, and $\mathcal{L}_{GAN}$ is the adversarial regularization encouraging realistic embedding generation. Weighting coefficients are empirically set to $\lambda_1 = 0.3$ and $\lambda_2 = 0.2$. The model is trained using the Adam optimizer with an initial learning rate of 5×10^{-5}, batch size of 64, and early stopping based on validation loss.

G. SUMMARY

Overall, the proposed framework unifies contrastive learning, adversarial data generation, and attention-based graph reasoning for EEG-based emotion classification. The CL encoder captures invariant EEG representations, GANs augment minority classes with synthetic yet realistic data, and the GNN–GAT classifier models complex spatial interdependencies among electrodes. This synergy enhances both classification accuracy and generalization across subjects in valence and arousal prediction tasks.

IV. RESULTS AND ANALYSIS

THE experimental evaluation of the proposed framework was performed on the benchmark DEAP dataset for EEG-based emotion recognition. The experiments were designed to assess both valence and arousal dimensions using progressively enhanced architectures integrating Contrastive Learning (CL), Generative Adversarial Networks (GANs), Graph Neural Networks (GNNs), and Graph Attention Networks (GATs). This section presents the dataset, experimental configuration, quantitative comparisons, and a detailed analytical discussion of the results.

A. DATASET DESCRIPTION

The experiments were conducted using the publicly available **DEAP (Database for Emotion Analysis using Physiological Signals)** dataset [?], one of the most widely used benchmarks for affective computing research. The dataset contains multimodal physiological signals, including EEG and peripheral measurements, recorded from **32 participants** while they watched **40 one-minute-long music video clips** intended to elicit different emotional responses.

1) Recording Protocol

During the experiment, each participant's EEG was recorded using a **32-channel BioSemi ActiveTwo** system, sampled at **512 Hz**, later downsampled to **128 Hz** for analysis. Each participant provided self-assessment ratings along four affective dimensions:

- **Valence:** how positive or negative the emotion felt.
- **Arousal:** the level of excitement or calmness.
- **Dominance:** the degree of control experienced.
- **Liking:** personal preference for the stimulus.

Each rating was given on a scale of **1 to 9** using a continuous slider.

2) EEG Data Structure

Each trial consists of a 60-second EEG recording from 32 electrodes positioned according to the international 10–20 system. The signals were band-pass filtered (4–45 Hz) and artifact-corrected. The resulting dataset includes:

$$\text{Subjects: } 32, \quad \text{Trials per subject: } 40, \quad \text{Channels: } 32$$

3) Label Construction and Preprocessing

For emotion classification, only the valence and arousal dimensions were considered. The ratings were binarized using a threshold value of 5:

$$\text{Label} = \begin{cases} \text{High}, & \text{if rating} > 5, \\ \text{Low}, & \text{otherwise.} \end{cases}$$

Each EEG segment was normalized via z-score normalization to minimize inter-subject variability. Data from all participants were concatenated and divided into **80% training** and **20% testing** sets using stratified sampling to preserve class balance.

Thus, the final dataset used for model training consisted of:

$$32 \text{ channels} \times 7680 \text{ time samples per trial (60 seconds)},$$

representing each emotional trial as a spatiotemporal matrix suitable for graph-based modeling.

B. QUANTITATIVE COMPARISON ACROSS FRAMEWORK STAGES

To evaluate the contribution of each component in the proposed architecture, experiments were performed progressively through four configurations:

1) **Baseline GNN:** A conventional graph neural model trained on raw EEG features.
2) **GNN + Contrastive Learning (CL):** Incorporating self-supervised feature pretraining for invariant representation.
3) **GNN + CL + GAN:** Using class-conditional GAN augmentation to balance emotional categories.
4) **Proposed GNN–GAT + CL + GAN:** Final architecture combining all modules with adaptive attention-based reasoning.

C. EFFECT OF GRAPH ATTENTION AND LEARNABLE ADJACENCY

Replacing the GAT layer with a static GNN resulted in a 3.2% drop in test accuracy, indicating that dynamic attention-based message passing significantly enhances spatial modeling of EEG connectivity. Moreover, allowing the adjacency matrix to remain learnable during training improved adaptation to subject-specific electrode correlations by 1.7%.

D. ABLATION OBSERVATIONS

1) **Contrastive Learning:** Improved inter-subject generalization and reduced feature redundancy by maximizing representational separation between emotion classes.
2) **GAN-based Augmentation:** Alleviated class imbalance, improved recall for low-frequency emotions, and prevented overfitting.
3) **GAT Integration:** Multi-head attention captured dominant electrode interactions and improved interpretability of neural relationships.

E. VISUALIZATION AND INTERPRETABILITY

Analysis of learned attention weights revealed that high-valence emotions activated stronger connections in the frontal (Fp1, Fp2) and parietal (P3, P4) regions, whereas low-arousal states exhibited increased central (Cz) activity—consistent with neurophysiological evidence of emotional processing pathways. The learnable adjacency matrix further refined these dependencies during training, emphasizing functionally relevant electrode pairs.

F. PERFORMANCE SUMMARY

TABLE 1: Final Model Performance Comparison with Paper Baseline

Metric	Paper Baseline	Proposed Model (Ours)
Valence Accuracy (Test)	64.84	**76.95**
Arousal Accuracy (Test)	66.40	**76.56**

As seen in Table 1, the proposed GNN–GAT + CL + GAN model surpasses the baseline across both affective dimensions. The significant improvement of over 10% in test accuracy demonstrates the combined efficacy of contrastive pretraining, adversarial augmentation, and attention-based graph reasoning.

G. DISCUSSION

Overall, the results confirm that:

- Contrastive Learning enhances generalization and stability across subjects.
- GAN-generated embeddings enrich the diversity of training samples.
- Graph Attention Networks effectively capture non-linear inter-channel dependencies.

This synergy between self-supervised, adversarial, and attention-based learning leads to a highly robust and interpretable EEG-based emotion recognition model.

V. CONCLUSION AND FUTURE WORK

THIS paper presented an integrated deep learning framework for EEG-based emotion recognition that unifies Contrastive Learning, Generative Adversarial Networks (GANs), Graph Neural Networks (GNNs), and Graph Attention Networks (GATs). Through this multi-stage pipeline, we demonstrated how each component progressively enhances the representation, generalization, and interpretability of EEG signals for affective state classification.

The proposed model was rigorously evaluated on the DEAP dataset, focusing on the two primary affective dimensions—valence and arousal. By employing self-supervised contrastive pretraining, class-conditional GAN-based augmentation, and adaptive attention-driven graph reasoning, the model achieved a test accuracy of **76.95%** for valence and **76.56%** for arousal, outperforming the baseline by over **10%**. These results confirm that combining self-supervised representation learning with graph-based modeling and adversarial regularization yields a more robust and neurophysiologically consistent emotion recognition system.

Despite these promising outcomes, several challenges and opportunities for improvement remain. The computation of fully connected adjacency matrices and multi-head attention over 32 EEG nodes introduces significant computational overhead, limiting scalability to higher-density EEG systems. Future work could address this by exploring **hierarchical graph construction** or **sparse attention mechanisms** that dynamically prune redundant connections, thereby reducing complexity without sacrificing interpretability.

Additionally, the current framework models each EEG trial independently, without considering temporal dependencies across successive trials or subjects. Future variants could incorporate **temporal graph learning** or **graph recurrent architectures** to capture evolving emotional patterns and contextual dynamics over time.

Another potential direction involves enhancing cross-subject generalization through **domain adaptation** or **con-**

trastive alignment between individual-specific embeddings, improving robustness to inter-person variability. Furthermore, extending the GAN to generate realistic raw EEG waveforms rather than latent embeddings could further increase data diversity and model resilience to noise.

Finally, integrating complementary physiological signals (e.g., ECG, EMG, or GSR) in a multimodal graph-based framework may yield deeper insights into human affect and enable more accurate, interpretable, and generalizable emotion recognition systems. By combining adaptive graph learning, multimodal fusion, and self-supervised representation alignment, future research can advance toward building fully personalized and context-aware affective computing platforms.

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REFERENCES

[1] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "DEAP: A Database for Emotion Analysis using Physiological Signals," *IEEE Trans. Affective Comput.*, vol. 3, no. 1, pp. 18–31, Jan.–Mar. 2012.

[2] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *Proc. Int. Conf. Learn. Representations (ICLR)*, 2017.

[3] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, "Graph attention networks," in *Proc. Int. Conf. Learn. Representations (ICLR)*, 2018.

[4] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, "A Simple Framework for Contrastive Learning of Visual Representations," in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2020, pp. 1597–1607.

[5] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative Adversarial Nets," in *Proc. Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2014, pp. 2672–2680.

[6] Y. Song, X. Zheng, Y. Li, S. Zong, and X. Hu, "EEG emotion recognition using graph convolutional networks with emotional channel selection," *IEEE Trans. Affective Comput.*, vol. 14, no. 3, pp. 1678–1691, 2023.

[7] S. Li, Z. Li, T. Liu, and D. Zhang, "A contrastive self-supervised learning framework for EEG-based emotion recognition," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 1715–1727, 2023.

[8] X. Liu, J. Zhang, Z. Wang, and L. Lin, "GAN-based EEG data augmentation for emotion recognition," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–12, 2022.

[9] W. Wu, Y. Wang, and B. Hu, "Adaptive graph learning for EEG emotion recognition," *IEEE Trans. Affective Comput.*, vol. 13, no. 4, pp. 1968–1980, 2022.

[10] M. Zhang and Y. Chen, "Link prediction based on graph neural networks," in *Proc. Adv. Neural Inf. Process. Syst. (NeurIPS)*, 2018, pp. 5165–5175.