

**GRAPH-THEORETIC AND GNN-BASED FRAMEWORK
FOR SURPLUS-DEMAND MATCHING IN ROOFTOP
FARMING NETWORKS**

BY

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Thesis titled “Graph-Theoretic and GNN-Based Framework for Surplus-Demand Matching in Rooftop Farming Networks”, submitted by SAJIA AFRIN, ID No: 242-25-032 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13-09-2025.

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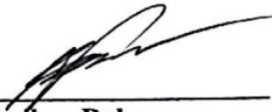
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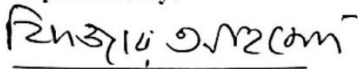
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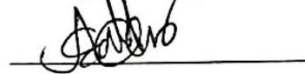
I hereby declare that, this project has been done by me under the supervision of **Dr. Fizar Ahmed**, Associate Professor, Department of CSE, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Rooftop farming has become an alternative model to improve urban food security and to make use of urban empty spaces. But the match between surplus supply and consumer demand is inefficient, leading to food waste and lost financial rewards. In this study, we propose a hybrid framework that utilizes both classical graph-theoretic algorithms and GNNs to enhance the surplus-demand matching problem in Dhaka city. A dataset consisting of the geographical, temporal and categorical characteristics of rooftop farming was compiled and studied. Baseline matches were obtained using classical methods such as Maximum Weight Bipartite Matching and link prediction heuristics. Later, GNN models—GCN, GraphSAGE, and GAT—were applied to predict potential links by learning node embeddings that capture spatial, temporal, and relational features. Comparative study based on model predictions, prediction accuracy, precision, recall, F1-score and ROC-AUC suggested that GNN-based models (especially GraphSAGE) achieved better prediction performance and flexibility than classical algorithms. The framework also developed recommendations for surplus-demand matching, optimized on the basis of geographical constraints. This study demonstrates how graph-based optimization and machine learning can be combined to enhance food distribution in cities, minimize waste and contribute to sustainability through rooftop food production.

Keywords: Rooftop Farming, Surplus-Demand Matching, Maximum Weight Matching, Graph Neural Networks, Graph Convolutional Network, GraphSAGE, Graph Attention Network, Link Prediction, Urban Agriculture

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Rapid urbanization in Dhaka has reduced potential agricultural land, and increased demand related to urban food systems. Rooftop farming has become a reality as a result, offering opportunities for residents to cultivate the likes of vegetables, fruits, and other products in vacant city spaces. Rooftop gardening is a part of household food security, an income generating activity, and as a means to environmental sustainability in urban centers [1, 2]. Despite the burgeoning rooftop farming, the inefficiencies in matching surplus production with consumer demand result in excessive food waste and unmet local demand [1,3].

Internationally, rooftop urban agriculture has been featured as part of resilient and sustainable food systems [4,5]. Efficient distribution of excess supply needs to be based on a model of supply and demand. This problem can be naturally formulated as a graph theoretic framework, where nodes represent supply and demand terms and edges are possible connections between supply-demand pairs [8,9]. Classical graph algorithms such as Maximum Weight Bipartite Matching (MWBM) have previously been used to optimize these pairings by maximizing the total match weight.

In recent times of deep learning, Graph Neural Networks have emerged as the state-of-the-art techniques to learn complex relational patterns in graphs [6,7,10,11]. GNNs model surplus-demand connections under the prediction by learning nonlinear spatial, temporal and relational dependencies compared with classical algorithms. Recent work has proven the capability of GNNs for supply chain optimization, product demand prediction, and bipartite graph matching [6, 7, 11, 12].

This research integrates both classical graph-theoretic methods and GNN-based approaches to design a robust recommendation system for Dhaka's rooftop farming. By leveraging MWBM, and advanced GNN architectures, the study aims to efficiently match

surplus agricultural produce with urban demand, thereby enhancing the sustainability and economic viability of rooftop farming systems.

1.2 Motivation

The rapid urbanization and the resultant stress on food supply chains have raised the importance of creative solutions to improve food access in the cities. Rooftop farming is proposed as a feasible and environmentally friendly solution to using vacant urban lots for food production while addressing the nutritional and economic needs of families. Yet, even as rooftop gardening becomes more popular, a key issue is how to best bridge the gap between excess produce and an urban market. Conventional distribution mechanisms have difficulty addressing difficult relations among producers and consumers. Meanwhile, emerging machine learning techniques, particularly Graph Neural Networks, offer promising opportunities to model such relationships and predict potential matches effectively. This research is motivated by the need to develop a hybrid framework that leverages both classical graph-theoretic methods and advanced GNN models to optimize surplus-demand matching, reduce waste, and support sustainable urban agriculture practices in Dhaka city.

1.3 Research Objectives

This framework aims to develop and assess systematic methodologies for optimizing surplus-demand matching in rooftop farming networks. The study specifically aims to:

- To study the nature of rooftop farming surplus and demand data (geospatial, temporal, and categorical).
- For performing baseline approach (MWBM) using classical graph algorithms.
- To create a graph-based characterization of surplus-demand relations with the spatial and temporal information.
- To apply GNN models (GCN, GraphSAGE, GAT) to link prediction tasks on bipartite graphs.

- To measure and compare the performance of such traditional graph algorithms against those of the GNN-based model in terms of standard evaluation metrics.
- To produce, visualize, and prioritize recommendations for surplus demand in rooftop agriculture that are practical for matching.

1.4 Research Questions

- RQ1: How can supply and demand of urban rooftop farming be efficiently synchronized to minimize waste and optimize resource use?
- RQ2: How well do classical graph algorithms (e.g., MWBM, Hungarian Algorithm) score in terms of efficient and interpretable surplus-demand matches.
- RQ3: How well are Graph Neural Networks (GCN, GraphSAGE, GAT) able to learn the complex spatial, temporal, and categorical relationships for the surplus-demand matching prediction?
- RQ4: How good is the performance and recommendation quality of GNN-based approaches compared to the traditional graph algorithms in the real-world?
- RQ5: What insights can be derived from these approaches to inform scalable, community-driven food exchange systems in urban agriculture?

1.5 Expected Output

- A plain structure of the surplus-demand dynamics in the context of rooftop farming at Dhaka.
- Classical graph algorithms for matching of surplus-demand.
- Graph-based representations of entries on both sides with enriched node and edge features.
- Implemented GNN models (GCN, GraphSAGE, GAT) trained for link prediction in bipartite surplus-demand graphs.
- Lists of recommended surplus-demand matches ranked by their matchability scores.
- Interactive visualizations of recommended matches on maps filtered by geographical distance thresholds.

- A practical framework can be defined as an approach that may support sustainable urban agriculture through the reduction of food waste accompanied by enhanced efficiency in distribution.

1.6 Project Management and Finance

Project management will follow a structured timeline. The financial requirements are minimal because the study relies primarily on computational resources, open-source libraries, and field-collected datasets. The methodology maintains rigor and practical applicability while minimizing costs.

Table 1.1: Project Management Table

Work	Time
Dataset	1 month
Literature Review	1 month
Experiment Setup	1 month
Implementation	2 months
Report	1 month
Total	6 months

1.7 Report Layout

Chapter 1: Presenting the work "Graph-Theoretic and GNN-Based Framework for Surplus-Demand Matching in Rooftop Farming Networks " and providing an overview of its motivation, objectives, expected outcomes, research questions and Project Management and Finance.

Chapter 2: In this section, I provide an overview of the related research, preliminaries/terminologies, research gap and challenges.

Chapter 3: I explain the research methodology.

Chapter 4: In this section, discussed experimental result.

Chapter 5: I discussed the impact on society, the environment, and the sustainability of this project.

Chapter 6: In this section, I have presented a comprehensive discussion and conclusion in addition to outlining the potential areas for future advancement.

CHAPTER 2

BACKGROUND

2.1 Preliminaries/Terminologies

Rooftop farming has become popular to improve urban food security and to make use of urban empty spaces. The match between surplus producer and consumer demand is necessary to reduce food waste. Entities and their relationships have been modeled using graph theory: entities as nodes and relationships as edges. More particularly, an exemplary case is a bipartite graph wherein two sets of surplus and demand nodes are connected between sets only. Algorithms such as MWBM help optimize matching in bipartite graphs with constrained allocations to make the allocation efficient.

GNNs are among the most suitable approaches for learning node and graph representations. Variants include Graph Convolutional Network (GCN), which generalizes convolution to graphs, GraphSAGE with neighborhood sampling applied for scalability, and Graph Attention Network (GAT) an attention mechanism prioritizing neighbors. Apart from that, since this research is considered the core of link prediction, estimating the likelihood of potential connections between surplus and demand nodes is described.

2.2 Related works

Rooftop gardening plays an important role in sustainable development around the world. In Dhaka, due to constraints on space and high density of population that do not allow for traditional cultivation, rooftop gardening is fast growing as a novel practice towards overcoming challenges related to food insecurity as well as income generation.

Dipannita et al. [1] emphasized that fruit rooftop gardening in the city of Dhaka provides a supplementary source of vegetables and fruits for consumption. It enables the urban households to get some extra income as well. This study reveals that the rooftop farmers are able to practice both subsistence consumption and local market sales, thus giving better household savings and dietary diversity. Roof top gardening practices all over Dhaka was

thoroughly reviewed by Chowdhury et al. [2] and finally concluded that this initiative has great potential towards food security in urban areas.

Challenges in rooftop agriculture from a scientific view were well articulated by Harada and Whitlow [3]. The status and trends of commercial rooftop farming across the globe documented by Mohareb et al [4]. Buehler & Junge [5] who emphasized resilient urban food systems. It noted that whereas in developed nations rooftop farming becomes more popular due to environmental awareness and the advanced technology

In recent years, the researchers pivoted towards integrating rooftop farming with technological innovations to make it more efficient and productive. Among the approaches, probably the most promising is through graph theory and neural networks known as GNNs. Wasi et al. [6] presented a detailed review of using GNNs in analyzing and optimizing supply chains, and found that GNNs learn the complex interrelationships within supply chains. Along fairly similar lines, Li et al. [7] used spatial GNN for product demand prediction and results indicated that spatial and relational information increases prediction accuracy.

Graph theory has a long history of applications between agricultural networking and social systems. Gołędzinowski and Błocki [8] stated that it is by using graph theory that social network analysis works; researchers appreciate relationships as well as interactions in complex networks through this perspective. Hossen et al. [9] applied a study on rural marketing of agricultural products from Bangladesh, and more particularly they showed that optimization using a graph reduced the inefficiency of product distribution as well as the links from farmers to markets. Ahmed et al. [10] studied the use of GNNs for product relationship prediction.

Utilizing a deeper understanding of the representation power of GNNs, more recent research also looks at optimization in bipartite graphs, which is directly also applicable to the supply/demand matching problem in rooftop gardening. Pan et al. [11] proposed

HybridGNN, which is a self-supervised model for handling the matching problem in graphs more effectively. Such models can also connect roof top gardeners (supply) with urban consumers or local markets (demand) leading to fair trade and lower transaction costs. Similarly, Özer et al. [12] studied link prediction in bipartite networks, and showed what future links or trades can be predicted based on history. Such a method could be also useful for urban farming platforms, when forecasting future demand trends or targeting new potential buyers is important to minimize food waste and increase economic benefits.

Taken together, these studies demonstrate that rooftop gardening in Dhaka can help enhance food security and generate new sources of income, although some structural and organizational challenges remain. At the same time, new advances in graph theory and graph neural networks may help address these challenges by making distribution more efficient, predicting demand, and strengthening supply-demand links. Combining sustainable urban agriculture with advanced computational tools is a new area of research that offers numerous opportunities in cities like Dhaka.

2.3 Research Gap

Rooftop farming is becoming more popular as a sustainable practice in cities. Most research so far has looked at its environmental impact, how it helps feed households, and its role in generating income. There is less information about how surplus produce is distributed to meet city needs. Often, there are no clear systems to connect producers and consumers, which can cause mismatches, food waste, and lower profits. While traditional graph algorithms like maximum weight matching have been used in similar areas, they have limits and for the complex factors that affect how surplus and demand interact. Newer methods, such as GNN, can work with relational data and predict connections in networks, but they have not been widely used for rooftop farming. This shows a need for a combined approach that uses both classic graph optimization and advanced machine learning to create better ways to match surplus with demand in urban rooftop farming.

2.4 Challenges

- **Geographical and Temporal Variability:** Matching must consider both spatial proximity and overlapping availability periods, which complicates the modeling process.
- **Scalability:** Handling large numbers of surplus and demand nodes efficiently, especially when using graph algorithms and GNN models.
- **Model Selection and Optimization:** Choosing suitable GNN architectures (GCN, GraphSAGE, GAT) for effective link prediction.
- **Practical Implementation:** Translating model predictions into actionable recommendations while considering real-world constraints such as delivery feasibility and local logistics.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This research falls under an issue of surplus and demand matching in the setting of rooftop farming within Dhaka city, Bangladesh. Rooftop agriculture has emerged as sustainability for meeting urban food security but mismatches between localized surplus and demands often take place, creating inefficiencies. Herein lies the assumption taken in this study that each rooftop user is a research unit who may either have surplus produce to contribute (supply) or express a need for specific agricultural items (demand). The tools used in instrumentation included Python Programming language and its libraries used for handling data: pandas, numpy; matplotlib, seaborn - visualization tools; folium - geospatial mapping library. The bipartite graphs and max weight matching were done using networkx in the traditional optimization method. The machine learning pipeline used scikit-learn for preprocessing including scaling and encoding. Advanced graph representation learning was implemented with PyTorch and PyTorch Geometric to design and train Graph Convolutional Network (GCN), GraphSAGE, and Graph Attention Network (GAT) models. These tools allowed both traditional and GNN-based approaches to the rooftop surplus-demand matching problem to be built, analyzed, and evaluated.

3.2 Data Preparation and Exploration

The primary data for this research has been collected manually from rooftop farming participants inside Dhaka city. The records comprise information such as user ID, location, item type-whether it is of demand or surplus-category, quantity, and exchange type, as shown in Fig 3.1. Basic data information is examined to understand the structure of the dataset.

User ID	Area	Type	Item	Category	Quantity (kg/bunches)	Latitude	Longitude	Exchange Type	Start Time	End Time
U0001	Mirpur	Surplus	Coriander	Herb	4	23.716745	90.360252	Scil	2025-09-17 08:00:00	2025-09-18 17:00:00
U0002	Badda	Surplus	Tomato	Vegetable	4	23.727919	90.410202	Scil	2025-08-26 11:00:00	2025-08-31 13:00:00
U0003	Gulshan	Demand	Mint	Herb	3	23.783777	90.384025	Swap	2025-08-26 12:00:00	2025-08-29 13:00:00
U0004	Mirpur	Demand	Spinach	Vegetable	6	23.772447	90.430713	Scil	2025-09-03 08:00:00	2025-09-14 14:00:00
U0005	Mirpur	Demand	Chili	Herb	4	23.784549	90.354582	Swap	2025-09-13 04:00:00	2025-09-14 07:00:00
U0006	Mirpur	Demand	Thyme	Herb	6	23.719518	90.385527	Scil	2025-08-28 11:00:00	2025-08-29 20:00:00
U0007	Uttara	Surplus	Mango	Fruit	7	23.732394	90.442539	Scil	2025-09-06 03:00:00	2025-09-10 15:00:00
U0008	Dhanmondi	Surplus	Spinach	Vegetable	7	23.732129	90.371098	Scil	2025-09-17 11:00:00	2025-09-20 14:00:00
U0009	Jatrabari	Demand	Marigold	Flower	5	23.716756	90.424499	Scil	2025-08-28 11:00:00	2025-09-01 17:00:00
U0010	Motijheel	Demand	Coriander	Herb	3	23.761143	90.359091	Swap	2025-09-16 01:00:00	2025-09-18 11:00:00

Figure 3.1: Sample Dataset

3.2.1 Data Analysis and Visualization

To gain insights multiple visualizations were generated:

Geographical Distribution: The distribution of rooftop garden users across different areas is visualized using a pie chart in Fig 3.2, providing insights into regional user concentration.

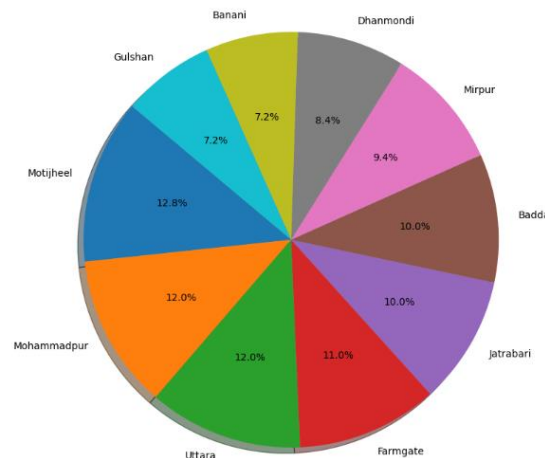


Figure 3.2: Pie chart of Geographical Distribution

Geospatial Visualization: User locations are visualized on an interactive map using the folium library, as shown in Fig 3.3. Markers are placed at each user's location, with popups displaying detailed information about their surplus or demand entry.



Figure 3.3: Map Visualization with pop-up details

Temporal Availability: The 'start' and 'end' columns are converted to datetime objects. The daily availability of items across the entire dataset is calculated and plotted as a time series, showing the fluctuations in the number of available items over time in Fig 3.4.

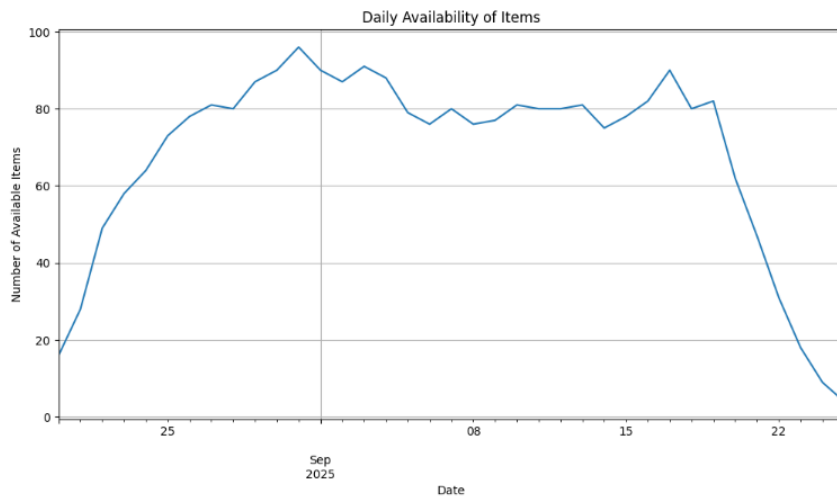


Figure 3.4: Time series plot of of items availability

3.2.2 Data Preprocessing: Relevant features are extracted, including numerical features (quantity, location coordinates, time duration) and categorical features (area, item, category, exchange type, node type). These features are preprocessed using StandardScaler and OneHotEncoder.

3.3 Traditional Graph-Based Matching

Maximum Weight Bipartite Matching: A bipartite graph utilized as a matching process to represent the potential connections between surplus and demand. Here's a breakdown of the logic:

Bipartite Graph Construction: Nodes were divided into surplus and demand sets. It has two sets of nodes (surplus, demand), and edges exist between nodes from different sets (i.e., a surplus node can only connect to a demand node). Each surplus entry from the dataset is represented as a node in one partition of the graph (labeled starting with "S_"). Each demand entry from the dataset is represented as a node in the other partition (labeled starting with "D_").

Edge Creation and Weighting: An edge is created between a surplus node and a demand node only if the following conditions are met: They involve the same item (e.g., Spinach, Cucumber). They belong to the same category (e.g., Leafy, Fruit, Vegetable). They have the same exchange type (e.g., exchange, sell). Their availability dates/times overlap for at least some duration. The weight of each edge is calculated as the inverse of the geographical distance between the locations of the surplus and demand entries. This means that closer pairs have a higher weight.

Maximum Weight Matching: Once the bipartite graph with weighted edges is constructed, the networkx.max_weight_matching algorithm is applied. This algorithm finds a set that: each surplus and demand node is matched at most once. The sum of the weights of the matched edges is maximized. In essence, this process identifies the most favorable pairings between surplus and demand based on the defined criteria and prioritizing closer geographical proximity.

Edge Weighting: Edge weights were defined as the inverse of geographical distance between surplus and demand locations (using the Haversine formula). This scheme prioritizes geographically closer matches.

Optimal Matching: The `networkx.max_weight_matching` algorithm was used to obtain a set of non-overlapping optimal matches that maximized the total weight.

Evaluation and Visualization: The resulting matches were analyzed by computing the average distance between matched pairs. A Folium map displayed surplus-demand links for visual inspection. Also, Fig 3.5 shows potential matches for a user.

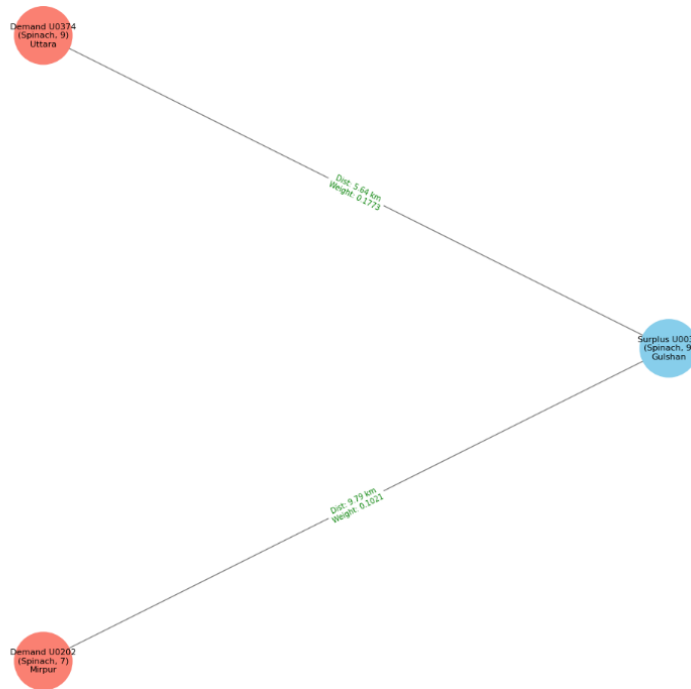


Figure 3.5: Potential Matches for a user using Maximum Weight Bipartite Matching

3.4 Graph Neural Network Framework

Beyond the traditional optimization approach, a data-driven deep learning method based on Graph Neural Networks (GNNs) was adopted. The matching problem was reformulated as a link prediction task, where the objective was to predict the likelihood of an edge existing between surplus and demand nodes.

3.4.1 Graph Representation

The bipartite graph was transformed into a homogeneous graph structure suitable for GNN libraries such as PyTorch Geometric. Each node, regardless of being surplus or demand, was mapped to an integer index. Edges were represented as bi-directional connections, carrying inverse-distance values as attributes. This conversion enabled the GNN models to learn embeddings for all nodes in a unified space.

3.4.2 Feature Engineering

To represent nodes meaningfully, a set of features was extracted:

Numerical features: quantity (kg), latitude, longitude, availability duration.

Categorical features: Rooftop area, item, category, exchange type, node type (surplus/demand). Categorical attributes were encoded using OneHotEncoder, while numerical features were standardized with StandardScaler. The final feature matrix served as input to the GNN models.

3.4.3 Model Architectures

Three widely used GNN variants were employed; these models produced low-dimensional node embeddings, which were later used to score potential links.

Graph Convolutional Networks (GCN)

Graph Convolutional Networks, or GCNs, are a key approach for deep learning with graph data. They take the concept of convolution, which is common in image analysis, and apply it to graphs. This helps the model understand both the features of each node and how the nodes are connected. GCNs are used in many areas, including social networks, recommendation systems, because they can learn useful information about nodes.

GCNs work by repeatedly gathering and updating information from each node's neighbors as architecture shown in Fig. 3.6. While GraphSAGE picks a set number of neighbors to

sample, GCNs use the whole graph's structure to share information at each layer. This approach helps features move smoothly between connected nodes and captures the overall structure of the graph.

The forward propagation rule for a single GCN layer is expressed as:

$$H^{(l+1)} = \sigma \left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \quad (3.1)$$

where:

- $H^{(l)}$ is the node feature matrix at layer l ,
- $W^{(l)}$ is the learnable weight matrix at layer l ,
- $\tilde{A} = A + I$ is the adjacency matrix with added self-loops,
- \tilde{D} is the diagonal degree matrix of \tilde{A} , and
- σ is a non-linear activation function (e.g., ReLU).

With this approach, each node updates its representation by combining its own features with the normalized features of its neighbors, as shown in (3.1). When several GCN layers are stacked, nodes can gather information from more distant neighbors, resulting in more detailed and useful embeddings.

In this study, GCN created node embeddings for the rooftop farming network graph. We feed features like location, crop type, and surplus or demand status into the GCN layers. This process produces embeddings that capture both the attributes and the structure of the network.

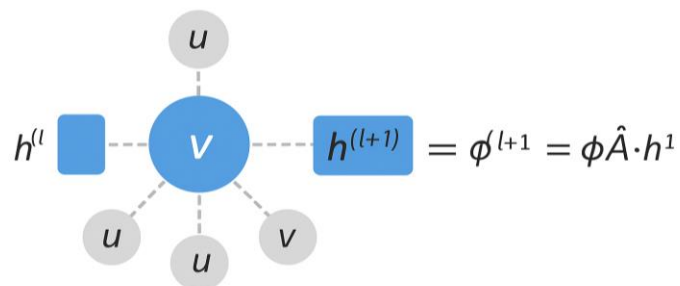


Figure 3.6: Proposed GCN Architecture

GraphSAGE

Graph Sample and Aggregate (GraphSAGE) is a graph learning algorithm that creates node embeddings by sampling and combining information from each node's neighbors, as shown in Fig.3.7. The fundamental process of GraphSAGE involves three main steps:

- **Neighborhood Sampling:** GraphSAGE samples a fixed-size set of neighbors. This sampling strategy ensures scalability for large graphs.
- **Aggregation:** The model combines information from the sampled neighbors using a defined aggregation function. This process enables the extraction of both structural and feature-based information from the local neighborhood.
- **Embedding Update:** The model combines the aggregated neighborhood information with the node's own features, then uses a neural network layer to update the node's embedding, as expressed in (3.2). By repeating this over several layers, the model learns from neighbors that are further away.

Mathematically, the embedding update at layer k for a node v can be expressed as:

$$h_v^k = \sigma\left(W^k \cdot \text{CONCAT}(h_v^{k-1}, \text{AGGREGATE}(\{h_u^{k-1}, \forall u \in N(v)\}))\right) \quad 3.2$$

where:

- h_v^k is the embedding of node v at layer k ,
- $N(v)$ is the set of sampled neighbors of node v ,
- $\text{AGGREGATE}(\cdot)$ denotes the chosen aggregator function,
- W^k is the trainable weight matrix at layer k , and
- σ is a non-linear activation function.

This study uses GraphSAGE to create low-dimensional node embeddings from the rooftop farming network graph. In this graph, each node is a user, either a producer or consumer, and edges show possible surplus and demand matches. GraphSAGE uses node attributes like location, crop type, and surplus or demand status, along with neighborhood information, to generate embeddings that keep both structural and feature details. These

embeddings are then used in the matching model to help make efficient and relevant crop redistribution recommendations within the network.

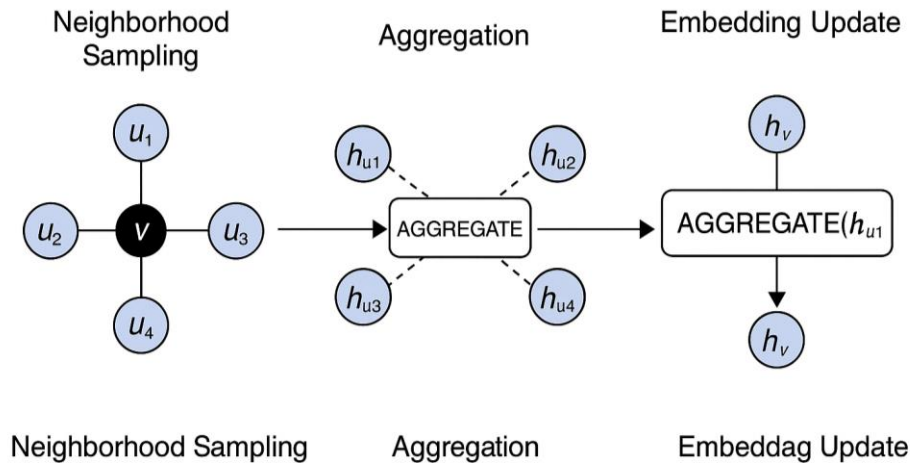


Figure 3.7: Proposed GraphSAGE Architecture

Graph Attention Network (GAT)

Graph Attention Networks, or GATs, build on graph neural networks by using attention mechanisms to give different importance to each neighboring node when gathering information, as shown in fig 3.8. While Graph Convolutional Networks (GCNs) treat all neighbors the same or adjust by their degree, GATs use learnable attention weights so the model can focus on the most relevant neighbors. This approach helps the model learn better representations, especially in graphs where some neighbors matter more than others.

The GAT framework operates in three main steps:

- **Feature Transformation:** Each node's feature vector is first linearly transformed through a learnable weight matrix.
- **Attention Mechanism:** For a pair of connected nodes i and j , an attention coefficient e_{ij} is computed to measure the importance of node j 's features to node i . This is typically done using a shared attention function $a(\cdot)$:

$$e_{ij} = a(Wh_i, Wh_j) \quad (3.3)$$

where h_i and h_j are the feature vectors of nodes i and j , and W is a learnable weight matrix.

- **Neighborhood Aggregation:** The coefficients are normalized across neighbors using a softmax function:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N(i)} \exp(e_{ik})} \quad (3.4)$$

Finally, the node representation is updated as a weighted sum of its neighbors transformed features:

$$h'_i = \sigma \left(\sum_{j \in N(i)} \alpha_{ij} Wh_j \right) \quad (3.5)$$

where σ is a non-linear activation function. Multi-head attention can be employed to stabilize learning by computing multiple independent attention mechanisms and combining their outputs through concatenation or averaging. Equations (3.3)– (3.5) show how GAT computes attention coefficients, normalizes them, and aggregates neighborhood information to update node embeddings.

In this study, we use GAT on the rooftop farming network graph to create node embeddings that reflect both features and structure, adjusting how much influence each neighbor has. Each node stands for a participant, either a producer or consumer, and edges show possible surplus and demand connections. The attention mechanism in GAT helps focus on the most important relationships, such as giving more weight to neighbors whose crop surplus matches another's demand. We then use these embeddings in our matching framework to make better surplus distribution recommendations.

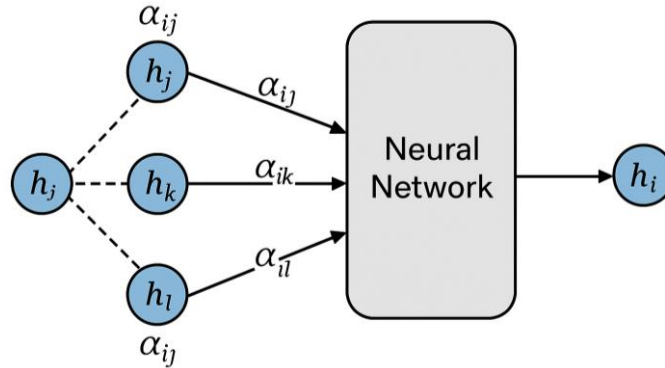


Figure 3.8: Proposed GAT Architecture

3.4.4 Training Objective: Link Prediction

The problem was modeled as a binary classification task at the edge level. Positive examples corresponded to surplus-demand pairs identified in the MWBM step, while negative examples were generated by sampling pairs that either violated matching criteria or were not selected in the optimal set. The RandomLinkSplit utility from PyTorch Geometric was used to generate balanced training, validation, and test sets.

During training, edge scores were computed using the dot product of the embeddings of node pairs. The models were optimized with Binary Cross-Entropy loss and the Adam optimizer. Performance was monitored using validation AUC-ROC and loss curves to avoid overfitting.

3.4.5 Evaluation Metrics

The trained models were evaluated on a dedicated test set using standard classification metrics:

Accuracy: Overall proportion of correctly predicted edges.

Precision and Recall: Indicators of the models' ability to correctly predict true matches without excessive false positives.

F1-score: Harmonic mean of precision and recall.

ROC-AUC: Measures discriminatory ability between true and false links.

Confusion matrices and ROC curves were also plotted for deeper diagnostic analysis. A comparative bar chart was generated to illustrate test accuracies across GCN, GraphSAGE, and GAT models.

3.4.6 Recommendation Generation and Post-Filtering

After training, the GNN models were used to generate matchability scores for all possible surplus-demand pairs in the dataset. These scores were ranked to create a list of recommended pairings, potentially extending beyond the rigid constraints of the MWBM baseline.

Recommendations: The trained GNN generated embeddings for all nodes. Matchability scores were computed using the dot product of surplus-demand embeddings, in equation (3.6). These embeddings are designed to capture the relevant features and relationships of each node within the network.

$$\text{Matchability Score} = \text{Embedding}(\text{Surplus}) \cdot \text{Embedding}(\text{Demand}) \quad 3.6$$

If the embeddings of a surplus node and a demand node are similar (point in roughly the same direction in the embedding space), their dot product will be high, indicating a strong potential match. If their embeddings are dissimilar (point in different directions), their dot product will be low, indicating a weak potential match. A ranked list of potential matches was produced.

Map Visualization: Recommendations were plotted on an interactive map as shown in Fig 3.9, with connecting lines between matched nodes.

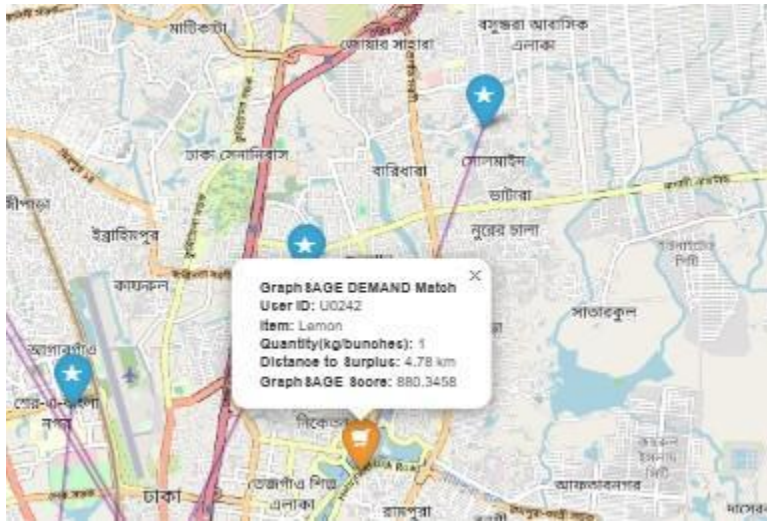


Figure 3.9: Map Visualization of link prediction

Distance-Based Post-Filtering: To ensure that recommendations remain practical and contextually relevant in an urban setting, a post-filtering mechanism was applied after the initial matching results. Specifically, only those surplus–demand pairs located within a 5 km geographical radius were retained, as shown in Fig 3.10. This filtering step reflects real-world considerations such as transport cost, freshness of produce, and feasibility of exchange within a dense urban environment like Dhaka. By applying this spatial constraint, the system prioritizes local matches, thereby reducing carbon footprint, minimizing logistical complexity, and increasing the likelihood of successful transactions. While the initial MWBM and GNN models generate optimal or predicted connections based on weight, availability, and product type, the post-filtering process ensures that only geographically feasible recommendations are presented to end users.

Top 10 Filtered GraphSAGE Recommendations (within 5 km):

	surplus_userid	surplus_item	surplus_quantity	demand_userid	demand_item	demand_quantity	distance_km	graphsage_matchability_score
0	U0337	Lemon	4	U0242	Lemon	1	4.777049	880.345764
1	U0020	Beans	6	U0005	Chili	4	1.434651	830.168264
2	U0089	Marigold	5	U0005	Chili	4	2.653338	793.882446
3	U0047	Chili	8	U0005	Chili	4	2.549061	757.856995
4	U0020	Beans	6	U0348	Marigold	6	4.671716	756.267292
5	U0268	Marigold	8	U0297	Beans	7	2.188434	747.777832
6	U0412	Lemon	9	U0242	Lemon	1	2.454304	739.661438
7	U0337	Lemon	4	U0042	Lemon	8	2.113328	730.903259
8	U0089	Marigold	5	U0348	Marigold	6	4.684958	730.278748

Figure 3.10: Distance-Based Post-Filtering

3.5 Summary of Methodology

This approach combines graph-theoretic optimization and machine learning on graphs to solve the rooftop farming surplus-demand matching problem. The maximum weight bipartite matching method provides clear and optimal baseline solutions. Graph neural networks use detailed graph features to find hidden relationships and offer flexible recommendations. Together, these methods enable both reliable baseline matching and scalable, data-driven suggestions for urban agriculture. Methodology flowchart:

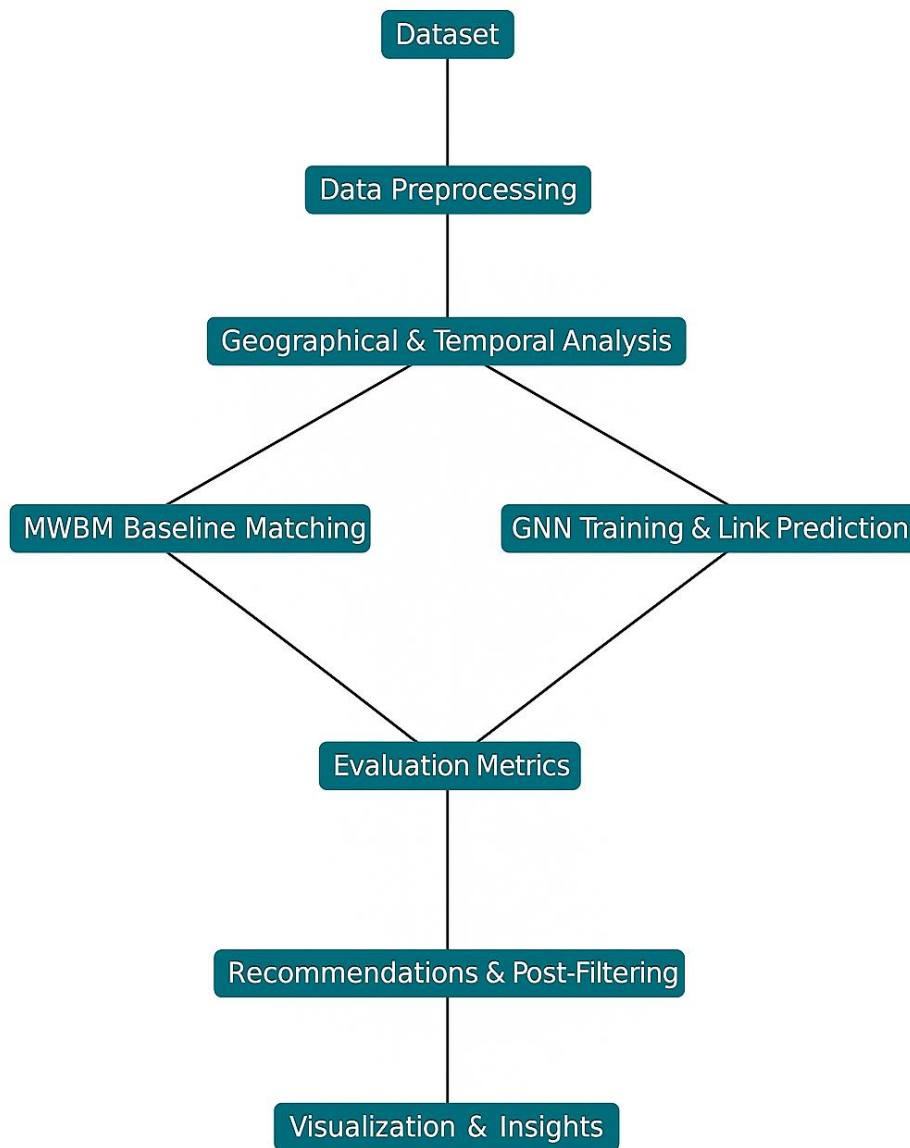


Figure 3.11: Methodology Flowchart

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The experimentation environment was developed in Python, using the pandas and numpy to work with data, the networkx to optimize graphs and the PyTorch Geometric to train GNN models. All the experiments are performed on an onboard workstation with 16GB RAM, an Intel i7 processor and GPU, which allows the fast training and testing of the model. The dataset were preprocessed and cleaned (categorical encoding, numerical scaling, and temporal formatting). The attribute 'location' was indicated with latitude and longitude, and other item-related attributes (type, category, amount and time) were represented appropriately. It used two primary approaches: traditional optimization based on Maximum Weight Bipartite Matching (MWBM) and machine learning techniques implemented using GNNs such as GCN, GraphSAGE, Graph Attentive Networks. The traditional matching method functioned as both a baseline and a source of positive examples for GNN training. GNN models were trained for link prediction to learn embeddings for surplus and demand nodes and to predict the likelihood of valid connections between them.

4.2 Experimental Results and Analysis

4.2.1 Maximum Weight Bipartite Matching (MWBM)

Matching Rate: 44.96% of surplus–demand pairs were successfully matched, indicating that while the model can identify feasible connections, nearly half of the supply remained unmatched due to strict constraints.

Average Distance: In Fig 4.1, The average distance between matched producer and consumer nodes was 5.03 km, the model favored geographically closer matches but still involved medium-distance allocations in certain cases.

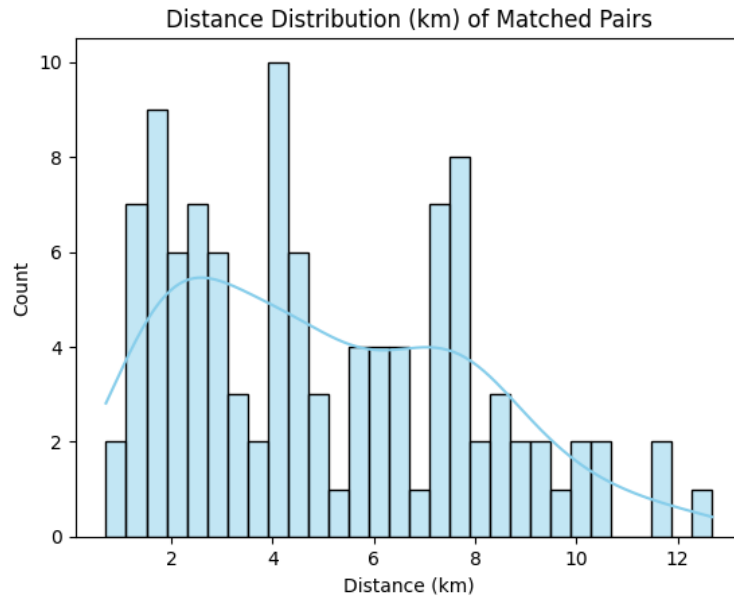


Figure 4.1: Distance distribution of matched pairs in MWBM

Average Availability Gap: The average mismatch in start dates between supply and demand was 1.8 days as shown in Fig 4.2, further optimization is possible.

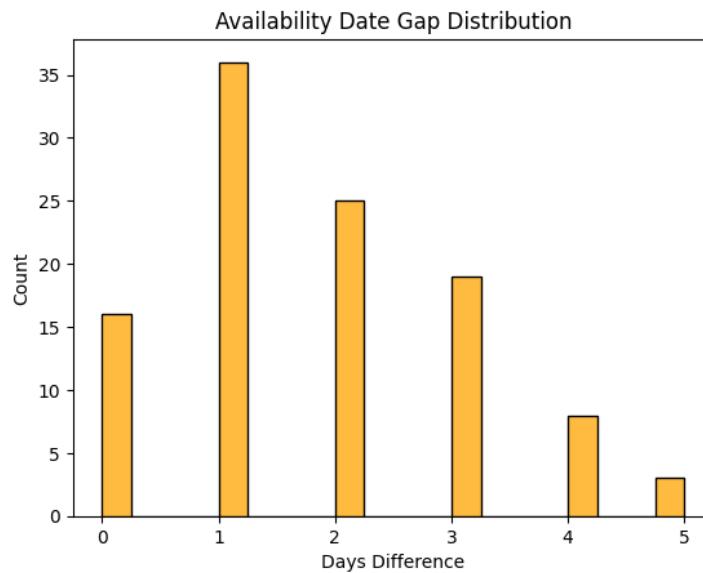


Figure 4.2: Availability date gap distribution

Quantity Match Ratio: On average, 80.3% of surplus quantities could be matched to demand, highlighting the model's efficiency in minimizing wastage.

Overall matching rate reflects limitations in handling dynamic availability and heterogeneous product categories, motivating the exploration of learning-based methods such as Graph Neural Networks (GNNs) for improved performance.

4.2.2 GNN Based Link Prediction

The comparison of test set accuracies for the three Graph Neural Network models demonstrates clear differences in their predictive performance. The GraphSAGE model achieved a strong capability to correctly predict potential matches. The Graph Convolutional Network (GCN) achieved a moderate accuracy. In contrast, the Graph Attention Network (GAT) performed the lowest, suggesting that while the attention mechanism captured some neighborhood information. Overall, the results highlight that GraphSAGE outperforms both GCN and GAT models. Showed strong balance between true positives and false positives. Neighborhood sampling and aggregation contributed to higher predictive power, making it the most suitable choice for generating reliable match predictions in the rooftop surplus-demand scenario. GNN based recommendations Generated ranked lists of potential surplus-demand matches beyond MWBM constraints. Identified plausible matches not included in the strict one-to-one MWBM solution.

Accuracy: Accuracy quantifies the proportion of correctly classified samples relative to the total number of samples, providing an overall assessment of model performance..

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

Precision: Out of all positive predictions generated by the model, precision focuses on the percentage of true positive forecasts.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: Also known as sensitivity or true positive rate, recall is the percentage of true positive predictions made out of all truly positive samples.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

F1 rating: The F1 score is the harmonic mean of recall and precision.

$$F - 1 \text{ Score} = 2 * \frac{Recall * Precision}{Recall + Precision}$$

Performance Analysis

Accuracy

Figure 4.3 compares the accuracy of three models:GCN,GraphSage,GAT.

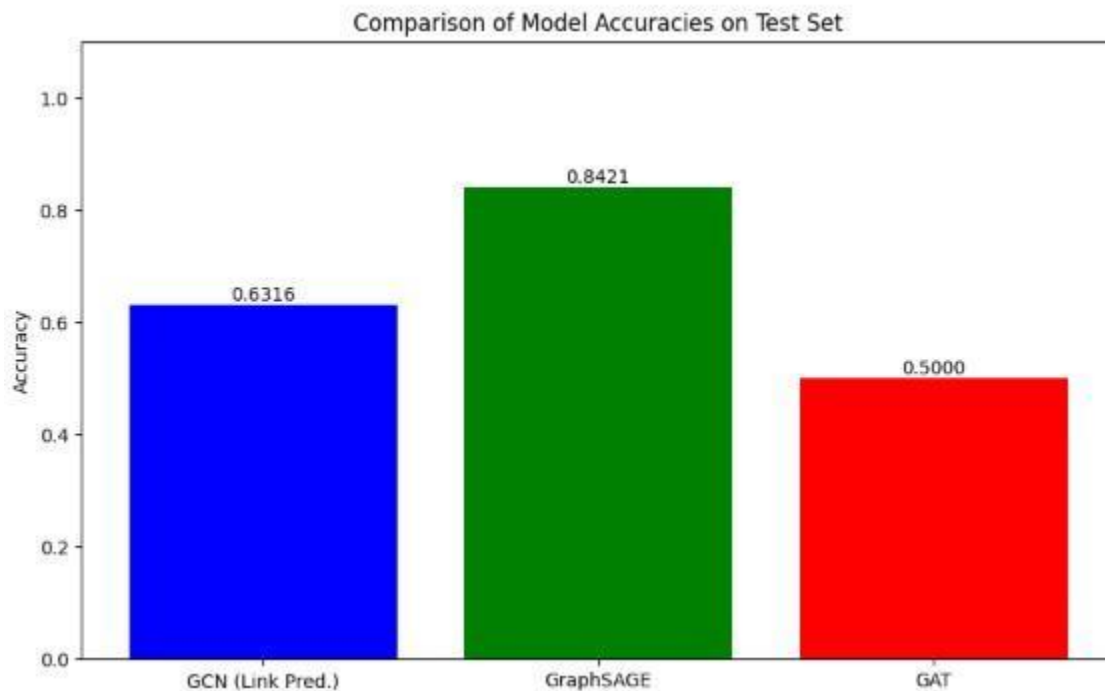


Figure 4.3: Accuracy Comparison of Models

The result compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 4.1:

Table 4.1. Performance Evaluation of all models

Model Name	Accuracy	Precision	Recall	F1-Score	AUC-ROC
GraphSage	0.8421	0.7600	1.0000	0.8636	0.9418
GCN	0.6316	0.6087	0.7368	0.6667	0.6717
GAT	0.5000	0.5000	1.0000	0.6667	0.8338

Graph Convolutional Network (GCN):

The GCN in Figure 4.4 results indicate that the GCN model achieves a balanced trade-off between precision and recall, with relatively higher recall, suggesting that it is more effective at capturing true existing links while tolerating some false positives.

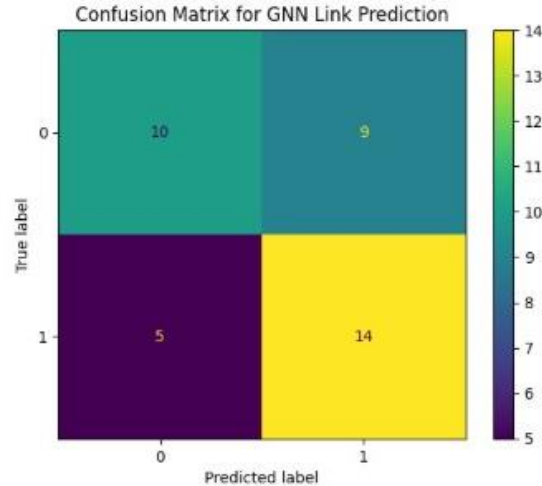


Figure 4.4: Confusion Matrix GCN

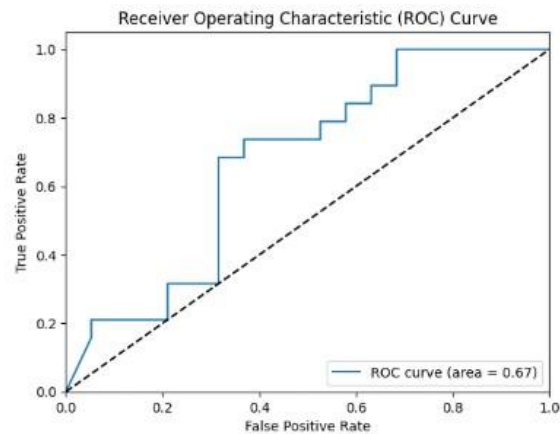


Figure 4.5: ROC Curve of GCN

Figure 4.5 shows that the ROC curve for the GCN model has an AUC of 0.67. It means better than random guessing, but not considered a strong score.

Graph Attention Network (GAT):

The model's overall accuracy is 50%, which is only marginally better than random guessing for a balanced binary set. This score is misleadingly low given the model's underlying capability as shown in Fig 4.6.

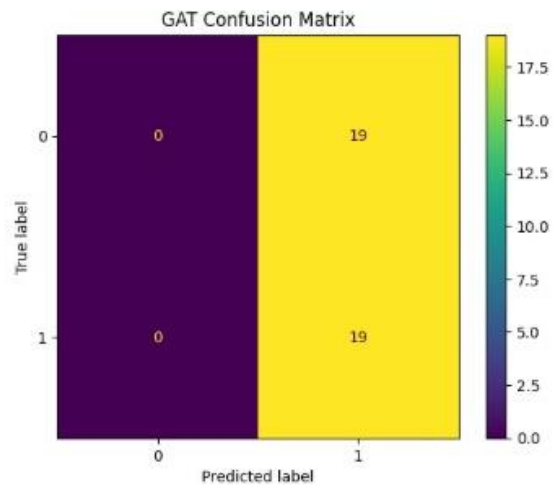


Figure 4.6: Confusion Matrix GAT

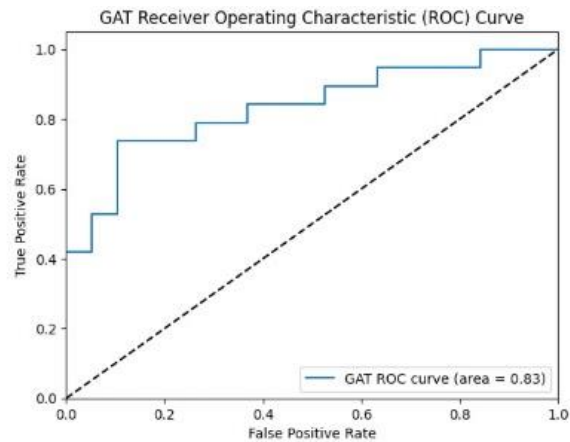


Figure 4.7: ROC Curve of GAT

Fig 4.7 shows that the high AUC score of 0.83 shows that the GAT model has learned useful patterns and can distinguish well between classes. The model is not performing poorly by design, but its current settings are not optimal. Overall, the GAT model has strong potential, but its default decision threshold needs better calibration.

GraphSage:

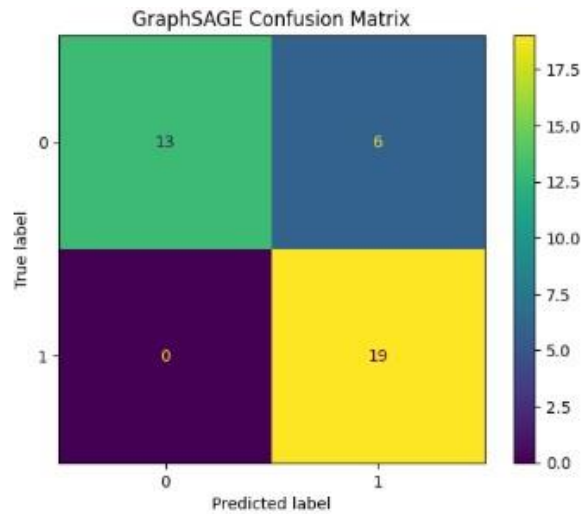


Figure 4.8: Confusion Matrix GraphSage

This performance profile suggests the model is well-suited for practical application. The high precision for Class 1 makes it excellent for scenarios where the cost of a false positive is high as shown in Fig 4.8.

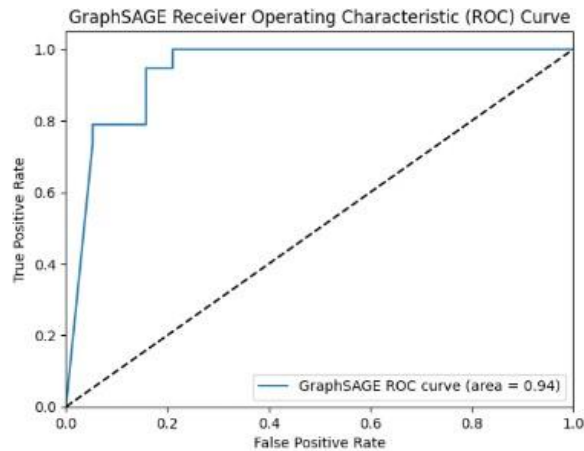


Figure 4.9: ROC Curve of GraphSage

Fig 4.9 shows that the ROC curve analysis shows an AUC score of 0.94, which means the model can completely separate the two classes.

4.3 Discussion

The experiments demonstrate the synergistic relationship between classical optimization and graph learning. The MWBM baseline provided consistent, interpretable, and optimal solutions under transparent criteria but suffered from being unable to scale for and one-to-one matching constraints resulted in many nodes unmatched. Graph Neural Network (GNN) models provide flexibility for learning complex node representations. Among these, GraphSAGE achieved the highest performance, as its neighborhood sampling approach addressed the surplus-demand problem effectively. Additionally, GNNs enable ranked recommendations, thereby enhancing matching opportunities. Overall, the MWBM_GNN framework demonstrates a balance between structured logic, as implemented by the Maximum Weight Bipartite Matching (MWBM) algorithm, and adaptability, as provided by GNNs, within the context of dynamic rooftop farming.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

The surplus-demand matching method for rooftop farms developed in this study could offer significant public benefits. By helping urban farmers share crops, it can improve food security and strengthen local food systems in crowded city areas like Dhaka. Closer collaboration between project teams and users can also help build a more active and supportive community. Rooftop farming as a social practice allows families to rely more on their own food, depend less on outside markets, and find new job opportunities. Using data-driven methods helps make resource allocation more transparent and fairer, so that extra produce meets local nutritional needs instead of going to waste.

5.2 Impact on the environment

Connecting producers and consumers through rooftop networks helps the environment by cutting production waste and making better use of urban rooftops. When more people use rooftop farming, cities can become cooler, the air can get cleaner, and there can be more green spaces. These improvements make local weather conditions better. Growing local crops also means cities rely less on food transported from far away. All of these steps help build a more sustainable and climate-resilient urban food system.

5.3 Ethical Aspects

This connection of surplus and demand in rooftop farming raises ethical concerns. It's important to ensure the resources are distributed equitably. Data privacy should not be compromised; production details cannot be shared without consent. Transparency on how algorithms make their decisions could help counteract bias in how crops are matched with

those in need and distributed. By taking on these ethical issues, we can establish trust and ensure that technology is, indeed, serving the community.

5.4 Sustainability Plan

When local farmers and households take part in activities like collecting data and exchanging crops, the system becomes more resilient. Using technology that is easy to scale and access also makes it easier to expand and keep costs down. The plan also calls for cutting food waste, encouraging organic methods and adding more greenery to rooftops as a way to boost city ecosystems. The project will be financially supported by local government, NGOs and private partners, to enable the project to continue and grow. Whilst inclusivity, transparency and resilience are identified as the tools to a lasting future as a model for communities and the city itself.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

This study presents a model to connect urban demand with excess rooftop farm produce in Dhaka. Created a database of surplus and demand (where and when and what kind of produce) and analysed the availability pattern and obstacles in linking producers and consumers. Traditional graph-theory-based approaches, such as Maximum Weight Bipartite Matching and link prediction, were implemented as baselines, tuning the matches by item, category, exchange type, and distance. We also tried Graph Neural Networks (GCN, GraphSAGE, GAT) to predict links between excesses and demands with node embeddings. Performance was assessed using Accuracy, Precision, Recall, F1-score, and ROC-AUC, and compared to traditional approaches. The results demonstrate that the combination of the graph-theory and GNN techniques offers effective and scalable solutions to problems in the domain of urban rooftop farming development.

6.2 Conclusions

This study shows that combining graph-theoretic methods with (GNNs) helps match surplus rooftop produce with local demand more effectively. Traditional methods like Maximum Weight Bipartite Matching provide solid baseline results, GNN models can better capture complex patterns. GraphSAGE stands out for its diversity and scalability. Both classical optimization and GNN-based learning makes this system more efficient, reduces waste, and supports sustainable urban agriculture.

6.3 Implication for Further Study

This study suggests multiple possibilities for further exploration in urban rooftop farming and graph-based modeling. The system can be improved by adding real-time information, seasonal and weather conditions, and crop spoilage to provide better insights. The same process used in the city could be applied elsewhere – making for more sustainable systems, and less waste. Overall, this work serves as a basis for intelligent and scalable methodologies that combine graph theory, machine learning, and urban agriculture.

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