

# Group 19: Cryptocurrency Price Forecasting

Shriyan, Hugo, Marcus





# Table of contents

**01**

## Background

About Cryptocurrencies

**02**

## Methodology

Our Approach

**03**

## Baseline Models

Implemented Other  
Models for Comparison

**04**

## Insights

Our Findings

**05**

## Limitations

Project Shortcomings and  
Future Work

**06**

## Conclusion

Summary of Our Work





A Digital Currency in Which Transactions Are Verified and Records Maintained By a Decentralized System Using Cryptography.

# Machine Learning Problem Statement



Price Prediction Using Historical Correlations

**01**

Objective 1

Develop a Graph-Based Model to accurately predict the future prices of various cryptocurrencies

**02**

Objective 2

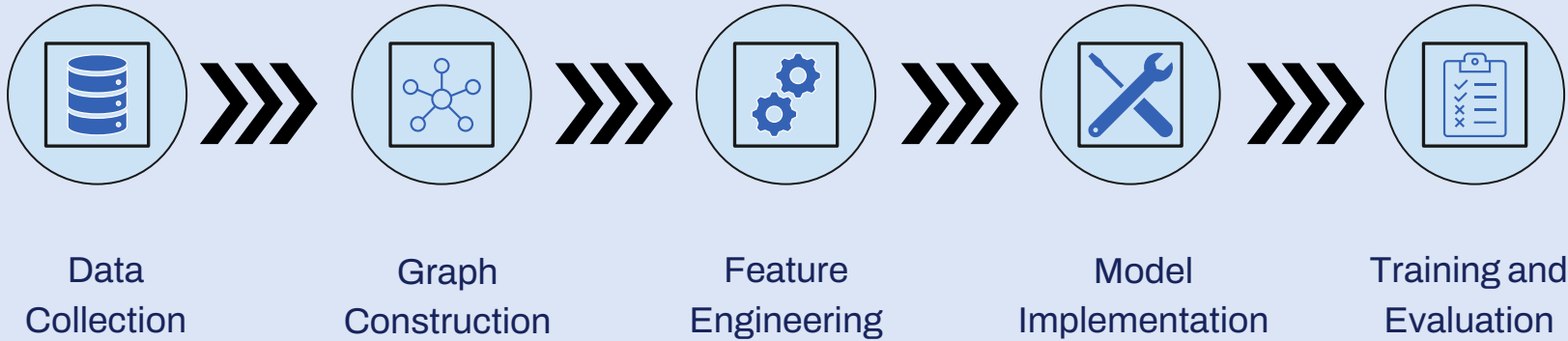
Use multiple features in the Graph-based model and add meaningful features to enhance performance

**03**

Objective 3

Implement baseline Graph models to compare our Model with.

# Methodology Overview



# Data Processing

Binance API



fetch\_data.py



Item Example

```
1499040000000, // Kline open time
"0.01634790",   // Open price
"0.80000000",   // High price
"0.01575800",   // Low price
"0.01577100",   // Close price
"148976.11427815", // Volume
"2434.19055334", // Quote asset volume
308,            // Number of trades
```

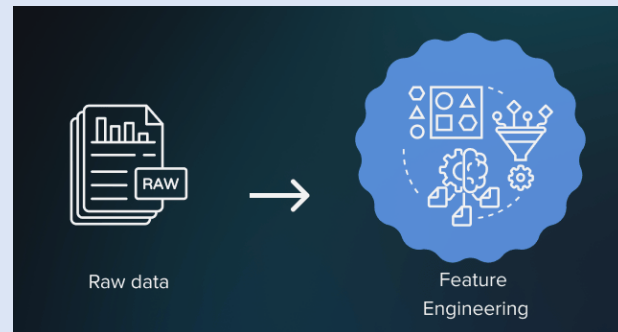


data\_loader.py



Select Parameters

main.py



Add New Features

# Feature Engineering

Features Added:

- Volume Quote Ratio
- Buy Sell Volume Ratio
- Buy Sell Quote Ratio
- Log Returns
- Stochastic Oscillator indicating momentum.
- Volume-Weighted Average Price
- Parkinson's volatility
- Garman-Klass volatility
- Average size of Trades
- Average Trade Quote Size

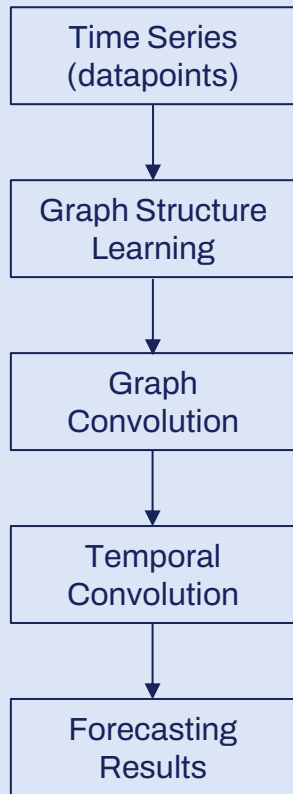
$$GKHV = \sqrt{\frac{1}{N} \sum_{i=1}^N \frac{1}{2} \left( \ln \frac{h_i}{l_i} \right)^2 - \frac{1}{N} \sum_{i=1}^N (2 \ln 2 - 1) \left( \ln \frac{c_i}{o_i} \right)^2}$$

$$ParkinsonHV = \sqrt{\frac{1}{4N \ln 2} \sum_{i=1}^N \left( \ln \frac{h_i}{l_i} \right)^2}$$

These features include liquidity metrics, price movement indicators, momentum indicators, volatility estimates, and trade behavior insights – all factors that can influence future price of a currency

# What is MTGNN?

## General Framework



### Graph Learning

$$\mathbf{M}_1 = \tanh(\alpha \mathbf{E}_1 \Theta_1)$$

$$\mathbf{M}_2 = \tanh(\alpha \mathbf{E}_2 \Theta_2)$$

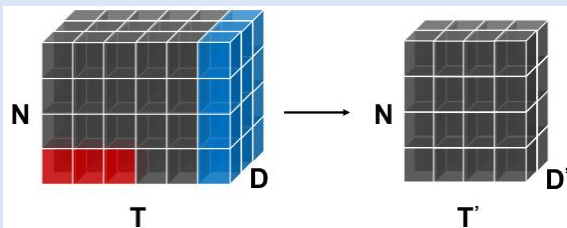
$$\mathbf{A} = \text{ReLU}(\tanh(\alpha(\mathbf{M}_1 \mathbf{M}_2^T - \mathbf{M}_2 \mathbf{M}_1^T)))$$

for  $i = 1, 2, \dots, N$

$$\text{idx} = \text{argtopk}(\mathbf{A}[i, :])$$

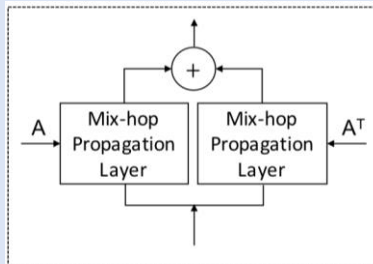
$$\mathbf{A}[i, -\text{idx}] = 0,$$

### How GC and TC works

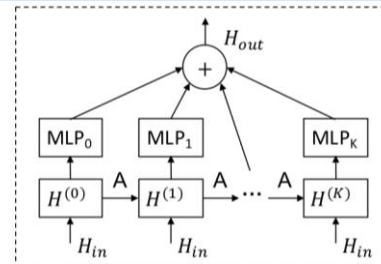


Red = TC filtering, Blue = GC filtering

## Graph Convolution

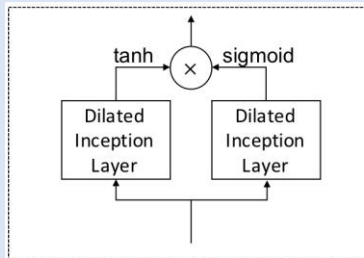


(a) GC module

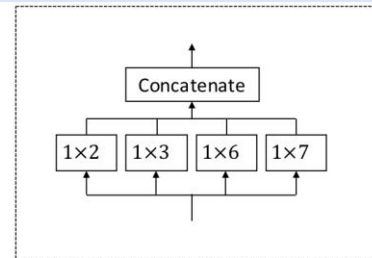


(b) Mix-hop propagation layer

## Temporal Convolution



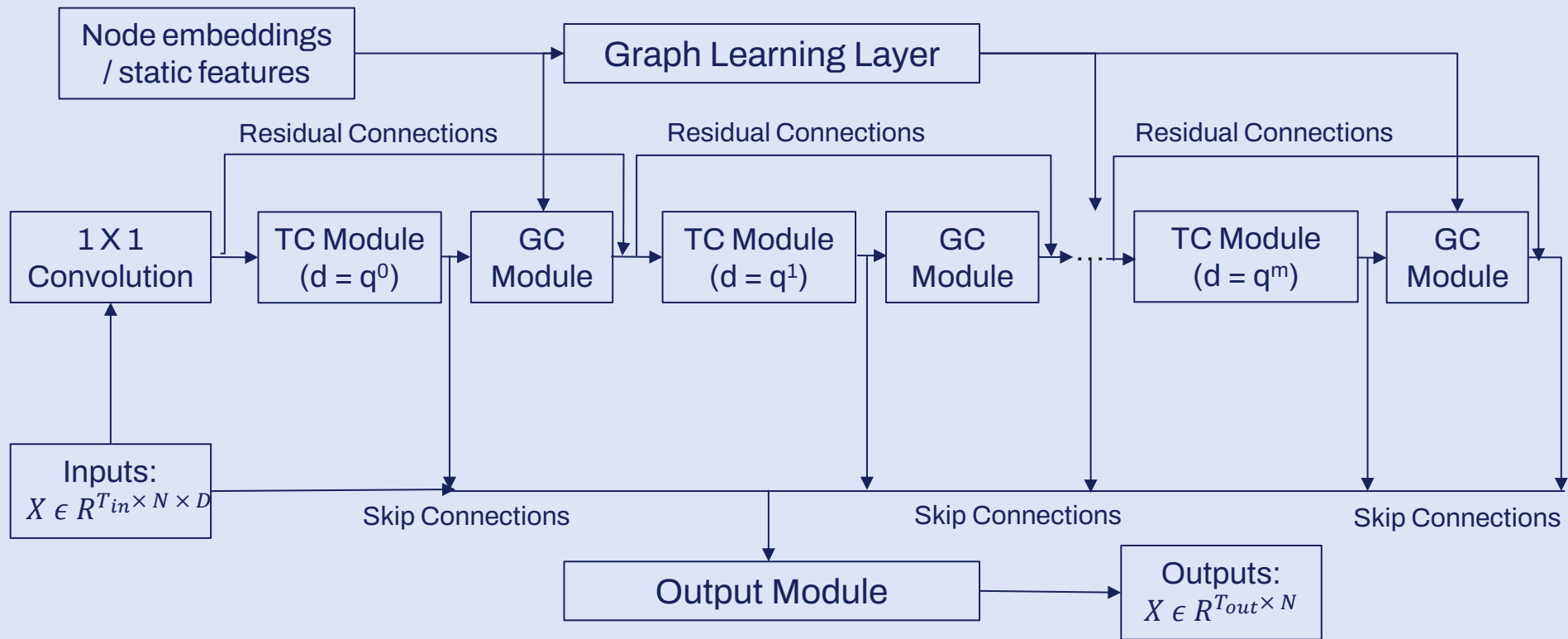
(a) TC module



(b) Dilated inception layer



# Model Architecture – Adapted from Paper



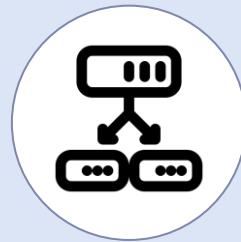
# Our Contributions



Attention Layer



Noise Removal



Resolve Data Leakage



Multiple Versions  
With Multiple Features



Baseline Models

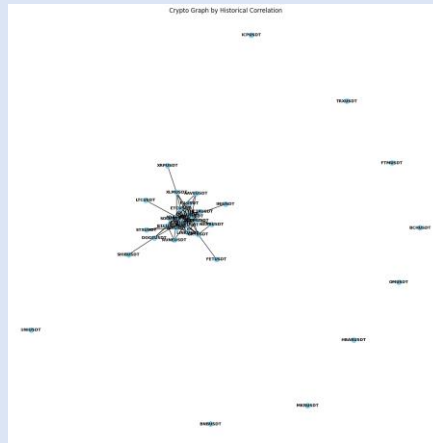
# Experiment Setup

- Learning Rate: 0.001
- Epochs: 16
- Optimizer: AdamW
- Batch Size: 16
- Ablation Study: Multiple features, Attention layer, Noise removal

**Date Range:** 2021/10/01 - 2024/10/01

**Timeframe of Training Set:** 1 Hour  
(27019 Samples per Currency) and 1  
Day (1108 Samples per Currency)

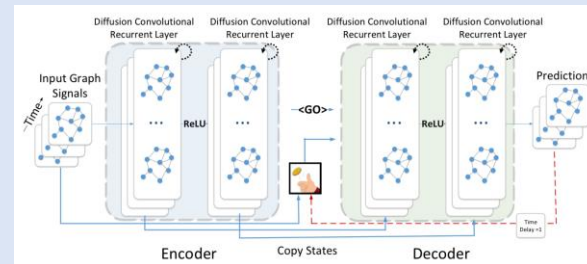
**Train-Test Split:** First 60% of the  
dataset for training, Next 20% for  
validation, last 20% for testing



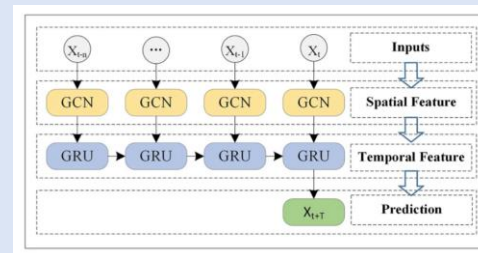
For Baseline Models, we  
initialized a Graph and  
Adjacency Matrix based on  
the correlation of  
currencies in 2024

# Baseline Models

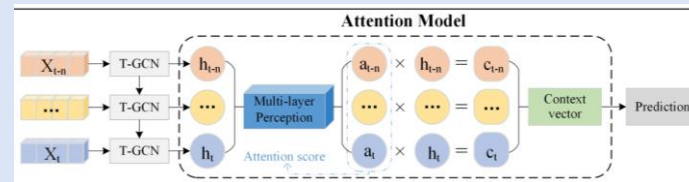
**DCRNN (Diffusion Convolutional Recurrent Neural Network)**



**T-GCN (Temporal Graph Convolutional Network)**



**A3T-GCN (Attention 3 T-GCN)**



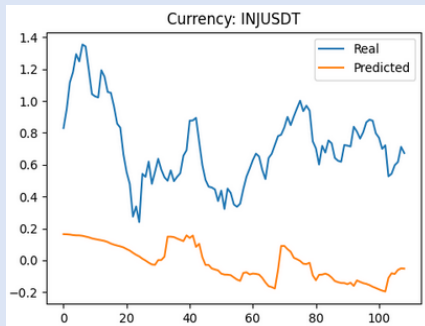
# Results – Baseline Models

Run details	Test Error	Test RMSE	Test RAE	Test CORR
T-CGN_1d	1458.4494	0.5929	0.6219	0.7289
A3T-GCN_1d	884.310	0.3931	0.5392	0.8241
DCRNN_1d	2472.27	0.8964	0.8674	0.3595
T-CGN_1h	7871.092	<b>0.2928</b>	<b>0.1772</b>	0.9360
A3T-GCN_1h	8497.078	0.3042	0.2328	<b>0.9417</b>
DCRNN_1h	51904.086	0.7519	0.8107	0.5655

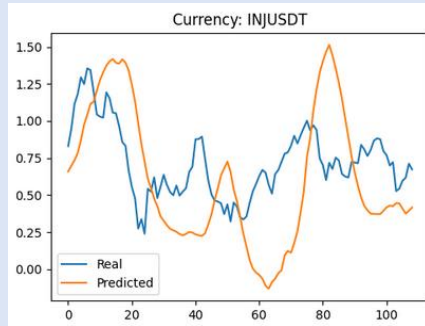
# Results - Baseline Models Visualization

Daily

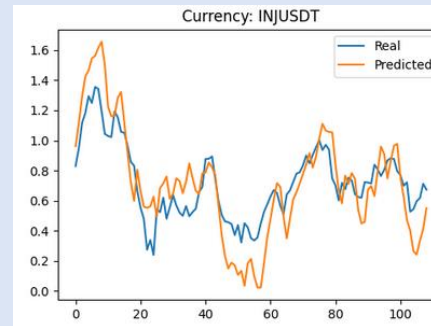
DCRNN



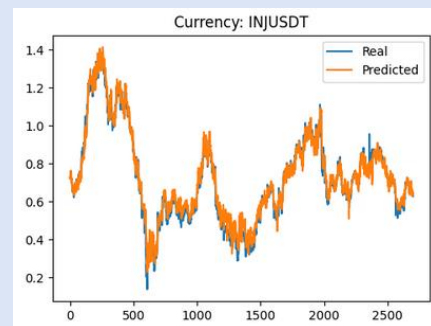
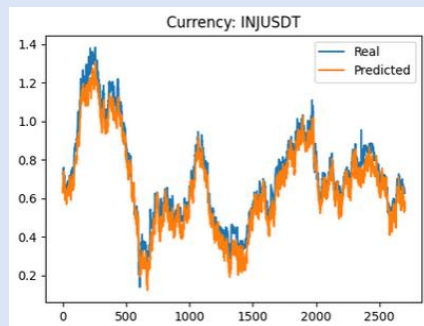
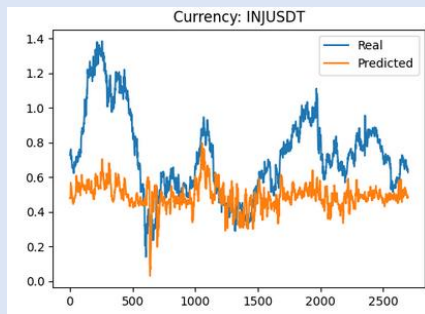
A3T-GCN



T-GCN



Hourly

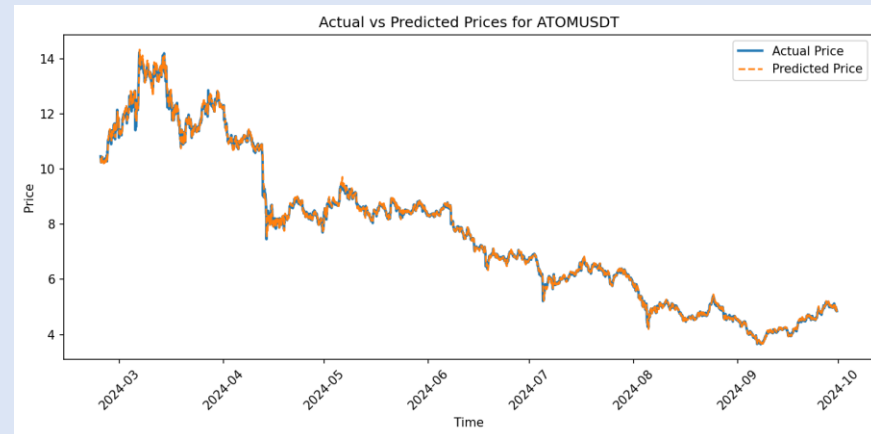
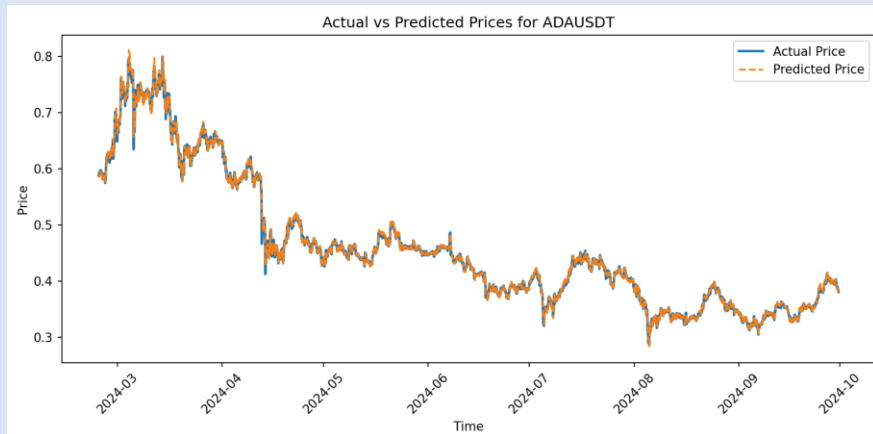
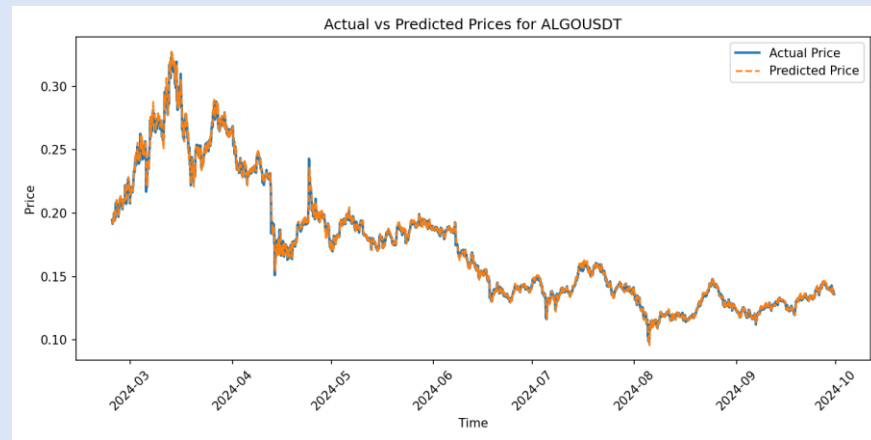
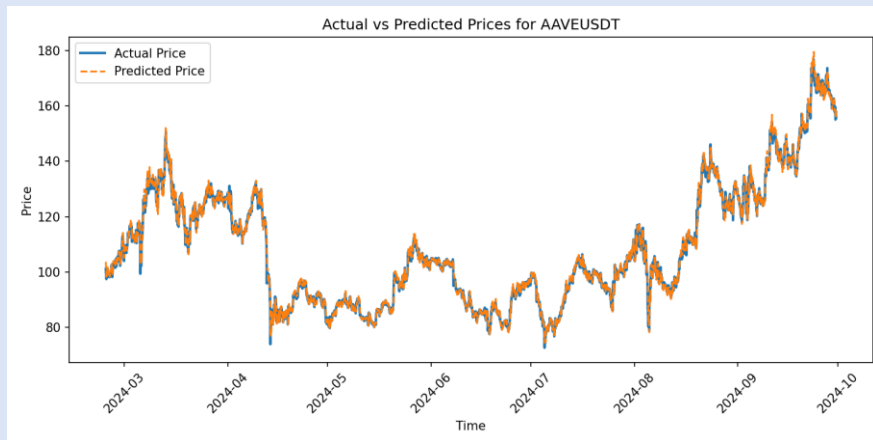


# Results - MTGNN

Run details	Test Error	Test RMSE	Test RAE	Test CORR
old_all_features_1h	686.432431	0.00242951	0.00021545	0.9950386
new_all_features_1h_attention	872.8712	0.00273965	0.00024256	0.99425787
new_all_features_1h	1293.12702	0.00333457	0.00029693	0.9919641
old_one_feature_1h	5966.82006	0.00716503	0.00288709	0.9979799
new_one_feature_1h	18007.9753	0.0124474	0.00514457	0.9946672
new_one_feature_1h_attention	20948.873	0.01342145	0.00552297	0.99392205
new_one_feature_1h_ma_attention	69975.6649	0.02452973	0.00665949	0.9873395
old_one_feature_1h_ma	73606.7123	0.02515811	0.00682768	0.9869195
new_one_feature_1h_ma	76468.436	0.0256425	0.00692622	0.9862451
old_one_feature_1d	1322001.6	0.10677032	0.04745535	0.7394306
new_one_feature_1d	1344669.62	0.10768181	0.05016395	0.667452

old = Original implementation, new = pytorch\_geometric implementation, one\_feature = Include close prices only

# Results – Best MTGNN Visualization





# Insights - Compare

- MTGNN has comparable performance on daily dataset without Adjacency Matrix to baseline models, meaning it was able to learn the correlation and dependencies between cryptocurrencies on its own.
- Performance is consistent across various features when using hourly data. Dataset size and shorter timeframe is the most important factor in determining prediction accuracy.
- MTGNN performed better than baseline models in every aspect, several reasons could be that the adjacency matrix it learnt captures interdependencies better than initializing a matrix. Additionally, the modules such as the mix-hop propagation contributes to overall performance

# Limitations, Future Scope and Conclusion

- Even though difference is low, the value of Bitcoin is so high that difference is 500. This can lead to inaccuracy.
- While we used moving averages to train our hourly models to capture long-term dependencies, in the future, we plan on using more sophisticated ensemble methods such as training a meta-model using the prediction results of models in varying timeframes.
- Therefore, our MTGNN model performs better on various metrics.