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International Journal for Modern Trends in Science and Technology
Volume 11, Issue 10, pages 43-49.
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol11issue10.html
DOI: https://doi.org/10.5281/zenodo.17272585

Graphical Neural Network-Based Target Selection Algorithm for ATM (Anti-Target Missiles) in Elliptical Formations

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To Cite this Article
Suma Priya. A & Dr. Lakshmi Bhavani. K (2025). Graphical Neural Network-Based Target Selection Algorithm for ATM (Anti-Target Missiles) in Elliptical Formations. International Journal for Modern Trends in Science and Technology, 11(10), 43-49. https://doi.org/10.5281/zenodo.17272585

Article Info
Received: 06 September 2025; Accepted: 04 October 2025.; Published: 05 October 2025.

KEYWORDS

Graph Neural Networks (GNN), Anti-Target Missile (ATM), Target Selection, Ship Formation, Pentagon, Hexagon, Elliptical Formation, MATLAB Simulation, Terminal Phase, Decoy Handling..

ABSTRACT

In the terminal phase of Anti-Target Missiles (ATM), choosing and identifying targets is a crucial task, particularly when the targets are positioned in ship formations with decoys and distortions. Although they work well for rigid alignments, traditional methods like Iterative Closest Point (ICP) and Modified ICP (MICP) have limitations when it comes to handling nonlinear distortions, decoy deception, and dynamic formation changes. This study proposes a target selection algorithm for ATM systems based on Graph Neural Networks (GNNs) to address these challenges.

Ship formations, such as Pentagon and Hexagon shapes, are modelled by the suggested method as graph structures, where ships serve as nodes and their spatial relationships form the edges. The GNN utilises relational learning and message passing to identify the intended target ship, removing the need for edge-based dependencies. Instead of relying on iterative point matching, the GNN employs relational learning and message passing to locate the target ship.

Three scenarios are analysed using MATLAB R2020a for simulation: (i) rigid formations, (ii) distorted formations, and (iii) distorted formations with decoys. The results show that the GNN technique maintains high success rates even under extreme distortion and decoy interference, achieving robust matching efficiency across all scenarios. For terminal-phase target selection in ATM applications, the proposed algorithm thus provides a reliable and adaptable alternative to ICP/MICP techniques.

INTRODUCTION

Since misidentification can result in mission failure, precise target selection during a missile's terminal guidance phase is essential in contemporary defence systems. The purpose of Anti-Target Missiles (ATM) is to differentiate the target ship from formations that contain noise, distortions, and decoys. Conventional techniques that rely on geometric point matching, such as Iterative Closest Point (ICP) and Modified ICP (MICP), are susceptible to noise and initial alignment.

Based on their capacity to represent geometric and relational dependencies in ship formations, this study suggests employing Graph Neural Networks (GNNs) for target selection in ATM systems. Without using iterative matching, GNNs are able to learn global formation patterns by representing ships as nodes and spatial relationships as edges. Simulations using MATLAB R2020a for rigid, distorted, and distorted-with-decoy scenarios show that the suggested method outperforms traditional techniques in terms of matching efficiency and robustness.

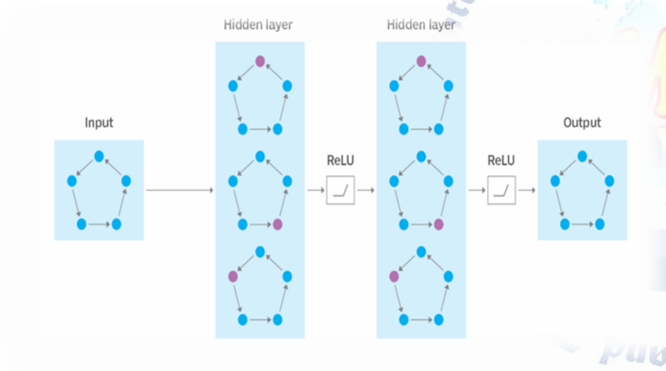

Fig 1: Basic Diagram of Graphical Neural Networks

2. RELATED WORK

As naval warfare scenarios become increasingly complex, extensive research has been conducted on target recognition and selection in missile guidance systems. Robust algorithms are crucial for terminal-phase guidance because ship formations frequently employ coordinated manoeuvres, distortions, and decoy deployment to deceive incoming missiles.

The Iterative Closest Point (ICP) algorithm is one of the most researched methods for aligning ship formations. ICP uses an iterative process to minimise the Euclidean distance between corresponding pairs to align two sets of points. However, ICP has issues with computational complexity, sensitivity to initialisation, and poor performance when there are significant distortions or false target insertions. A number of ICP modifications have been introduced to increase robustness.

2.1 Existing Method:

The need for a framework that can naturally model and learn from graph-structured data is highlighted by these limitations. Graph Neural Networks (GNNs) have become a promising paradigm in this respect. By allowing the integration of both node features (like ship coordinates) and edge features (like relative distance and angular separations), GNNs bring deep learning to graphs. Because GNNs directly learn structural patterns and relational dependencies, they are naturally resistant to decoys and robust to distortions, in contrast to ICP/MICP, which rely on iterative point-to-point alignment.

2.2 Novelty:

In this paper, we introduce a novel GNN-based target selection algorithm for Anti-Target Missiles (ATM). Unlike previous works that employ ICP or its modifications, our approach eliminates the need for iterative matching. Ship formations such as the Pentagon in Elliptical Shape and Hexagon in Elliptical Shape are modelled as graphs, and the GNN is trained to recognise the intended target under rigid, distorted, and decoy-infused conditions. This contribution represents a paradigm shift in missile guidance research, offering a scalable and adaptive alternative to traditional geometric alignment methods.

3. SYSTEM ARCHITECTURE

The Fire Control Radar (FCR), Seeker, and the GNN-based decision module are among the several subsystems integrated into the proposed Graph Neural Network (GNN)-based target selection algorithm for Anti-Target Missiles (ATM). Fig. 1 (Block Diagram) shows the entire system workflow.

- Data Acquisition for Fire Control Radar (FCR)

  The FCR records the relative position of ship formations during mid-course guidance. A collection of coordination points that represent potential targets within a specified surveillance area is the output.
- Input form seekers (Terminal Phase)

  The seeker improves target acquisition as the missile moves into the terminal phase by gathering high-resolution ship position data. This stage includes distortions brought on by environmental factors and electronic countermeasures.

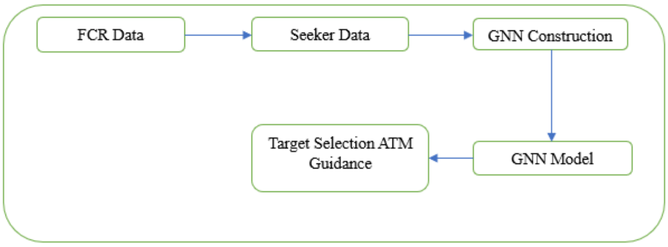

Fig 2: Block Diagram for System Architecture

- Module for Graph Construction

○ A node ($v_i \in V$) represents each ship in the formation.

○ Edges ($e_{ij} \in E$) are used to represent pairwise relationships, such as angular separations and inter-ship distances.

○ With X standing for node features (position, velocity, and RCS if available), the formation is thus represented as a graph G = (V, E, X).

- Target Selection Engine

Graph Neural Network - A multi-layer GNN uses message-passing operations to process the generated graph:

$$h_i^{(l+1)} = \sigma\left(\sum_{j \epsilon N(i)} f\left(h_i^{(l)}, h_j^{(l)}, e_{ij}\right)\right)$$

Where $h_i^{(l)}$ Is the embedding of node I at layer l, N(i) denotes the neighbours of node *i*, and *f(.)* is the learnable message aggregation function. To determine the intended target ship, a classification head processes the final node embeddings.

- Output of Decision
- The target index is produced by the GNN and sent back to the ATM's guidance and control system for interaction.

Elliptical Pentagon and Hexagon Formations Modelling

Two geometric ship formation configurations were modelled in MATLAB R2020a to assess the robustness of the suggested GNN-based method:

- Elliptical Pentagon:

Five target ships are placed roughly at a regular pentagon's vertices.

An elliptical scaling matrix transforms the entire formation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Where a and b are the ellipse axes scaling parameters.

- Elliptical Hexagon

A regular hexagon with six ships at its vertices.

Distortion effects are introduced using a similar elliptical transformation.

- Scenarios for Simulation

○ Rigid Formation: The perfect, distortion-free geometric configuration.

○ Distortion: Elliptical scaling and rotation are used in the distortion formations.

○ Distortion + Decoys: To mimic electronic countermeasures, more fictitious targets are injected into the formation.

4. GRAPHICAL NEURAL NETWORKS FOR TARGET SELECTION

Ship formation modelling in ATM systems is a good fit for Graph Neural Networks (GNNs), a class of deep learning models that work directly on graph-structured data. GNNs can represent non-Euclidean data, such as ship formations, where spatial and relational dependencies are crucial, in contrast to CNNs, which leverage Euclidean grid structures.

In this work:

Nodes: represent ships (or detections) obtained from FCR + Seeker fusion.

Node Features (x_i):

Position: (x_i, y_i)

Range (r_i) and bearing (θ_i)

Velocity or Doppler (r_i) if available

Radra Cross Section (RCS) or confidence level.

Edges (e_{ij}): represent pairwise spatial relations between ships, e.g.

Euclidean distance: $\|P_i - P_j\|$

Relative Angle: $\Delta\theta_{ij}$

Thus, a ship formation is represented as a graph:

$$G = (V, \varepsilon, \boldsymbol{X}, \boldsymbol{E})$$

Where $\mathcal{V}$ = set of nodes, ε = set the edges, X = node feature matrix, E = edge feature set.

Message Passing Framework

Message passing is where GNNs excel: each node updates its state by combining data from its neighbours.

At layer ℓ, the hidden state of the node i is updated as:

$$\boldsymbol{h}_i^{(l+1)} = \sigma\left(\boldsymbol{W}_1^{(l)} \boldsymbol{h}_i^{(l)} + \sum_{j \in N(i)} \varphi^{(l)}\left(\boldsymbol{h}_i^{(l)}, \boldsymbol{h}_j^{(l)}, \boldsymbol{e}_{ij}\right)\right)$$

Where:

$\boldsymbol{h}_i^{(l+1)}$: Feature vector of node i at layer l.
$N(i)$: neighbour of node i.
$\varphi^{(l)}$: edge update function
σ: nonlinear activation (e.g., ReLU).
$\boldsymbol{W}_1^{(l)}$: trainable weight matrix.
After L layers, the final node embeddings $\boldsymbol{h}_i^{(L)}$ They are used for classification:

$$\hat{y}_i = \text{Softmax}\left(\boldsymbol{W}_o \boldsymbol{h}_i^{(L)} + \boldsymbol{b}_o\right)$$

Where $\hat{y}_i$ Is the probability that node i is the true target?
The GNN thus outputs a target node index along with confidence scores.

5. PROPOSED METHODOLOGY

The suggested approach uses a Graph Neural Network (GNN)-based target selection algorithm for Anti-Target Missiles (ATM) in place of iterative ICP/MICP-based alignment. As illustrated in Fig. 2, the pipeline consists of four main stages.

- Data Generation:

○ Create the following ship configurations: Pentagon and Hexagon in an Ellipse
○ Include variations such as rigidity, distortion, and distortion with decoys.

- Graph Construction:

○ Every ship is a node.
○ Every pairwise relationship (velocity, angle, and distance) equals an edge.
○ Create a GNN adjacency matrix.

- GNN Training

○ Node and edge features as input
○ Node embeddings are updated by message passing layers.
○ Training under supervision using a labelled true target node.
○ Loss: Classification by cross-entropy

- Target classification:

○ Probability outputs from a trained GNN for every node
○ Choose the most confident target.
○ Enter the desired outcome into the ATM guidance module.

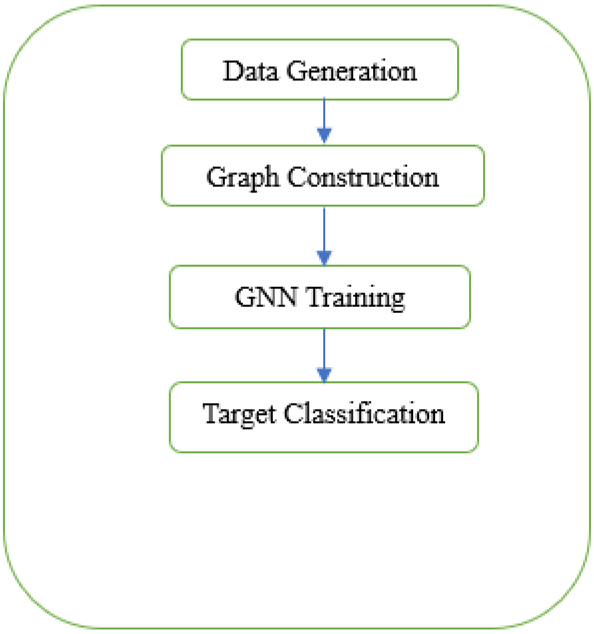

Fig: Pipeline for Proposed Methodology

6. RESULTS AND DISCUSSION

The effectiveness of the GNN-based target selection for the Pentagon formation is displayed in Table I.

S.no	Case	Matching Efficiency	Translation error	Rotation error
1	Rigid	100	0	60
2	Distortion	98.05	0.16	60
3	Distortion with Decoys	80.90	3.87	60

Table I: Pentagon and Ellipse Results

Observations:

- In the rigid formations, GNN learnt the formation structure and performed flawlessly.

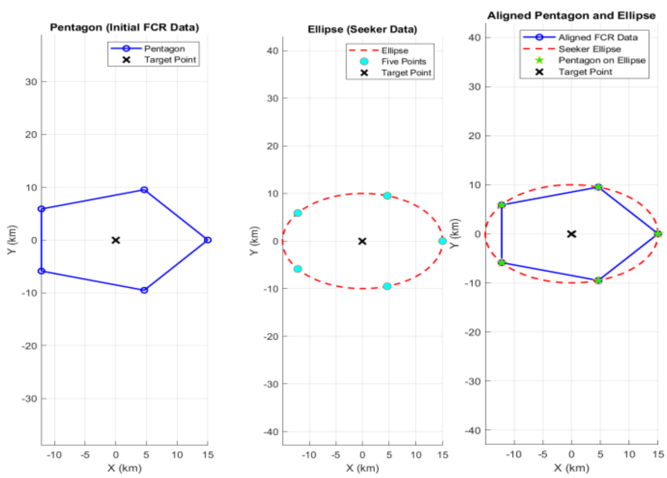

Fig 6.1(a): Rigid Formations

- The five ships are perfectly aligned on the boundary of an ideal ellipse without any measurement noise, distortion, or decoys.
- The inter-ship distances and angles are exactly according to the formation parameters (semi-major axis, semi-minor axis, orientation).
- The GNN easily learns and identifies the true target because the structure is consistent across all instances.

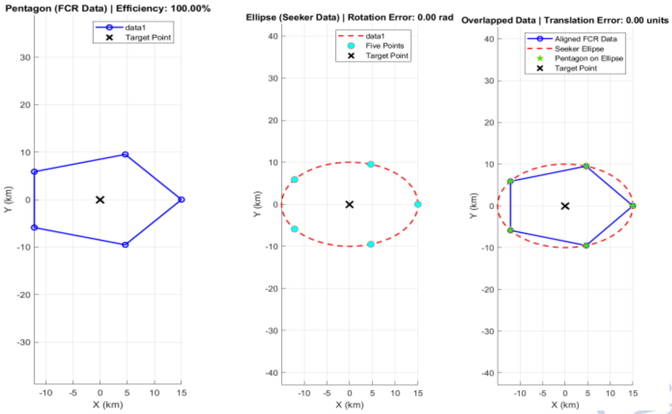

Fig 6.1(b) Distortion Formations

- In distortion, GNN maintained good efficiency.
- Nonlinear distortions of the elliptical Pentagon include random noise in measurements and uneven scaling along axes.
- Differences in the distances and angles between nodes are caused by slight variations in position and orientation.
- In contrast to ICP/MICP, which deteriorate because of their dependence on exact alignment, the GNN efficiently extracts relational patterns while maintaining a high matching efficiency despite the distortions.

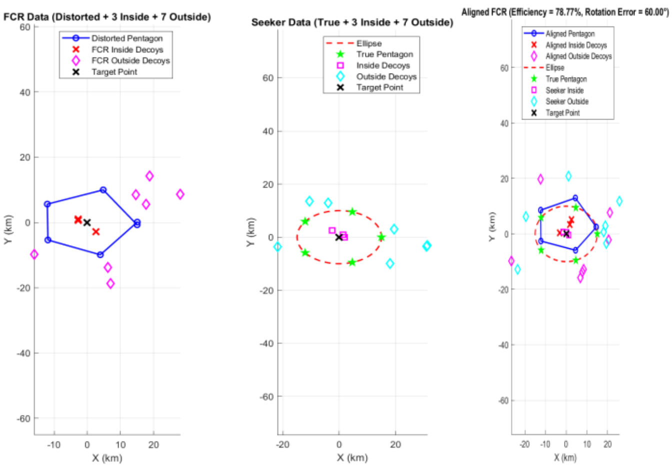

Fig 6.1(c): Distortion Formations with Decoys

- GNN demonstrated fewer false alignments and was more resilient even when using decoys.

- In addition to distortions, random decoy points are inserted near the formation, mimicking real targets to confuse the guidance system.
- The GNN's relational learning allows it to distinguish the true structure from false ones, significantly outperforming ICP/MICP methods that are prone to misalignment in the presence of decoys.

The effectiveness of the GNN-based target selection for the Pentagon formation is displayed in Table II.

S.no	Case	Matching Efficiency	Translation error	Rotational error
1	Rigid	100	0.14	0
2	Distortion	97.91	0.15	0
3	Distortion with Decoys	89.88	0.266	0

Table II: Hexagon and Ellipse Results

Observations:

- Similar to the Hexagon, GNN consistently outperformed.

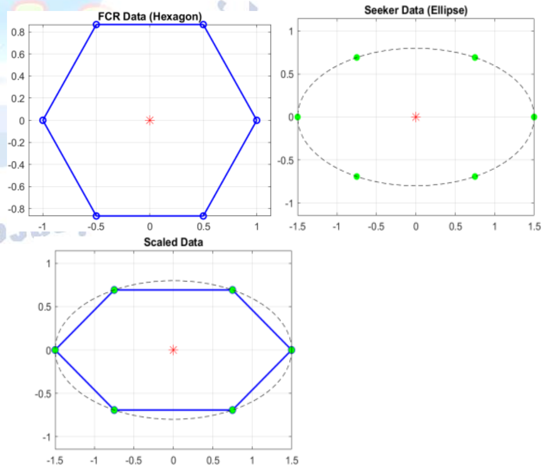

Fig 6.2(a) Rigid Formations

- An ideal ellipse is formed by six ships that are precisely positioned, oriented, and spaced apart.
- Because of the structure's symmetry and consistency, the GNN can identify the right target in every trial with almost perfect accuracy.

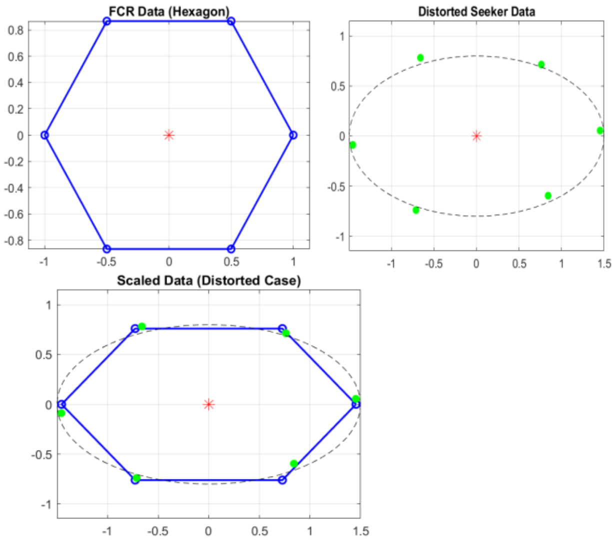

Fig 6.2(b) Distortion Formations

- To simulate sensor errors and manoeuvres, the formation undergoes distortions such as random measurement noise and slight geometric warping.

- While ICP/MICP finds it difficult to identify precise correspondences, the GNN uses the overall structure rather than individual points to provide robust classification despite distortions.

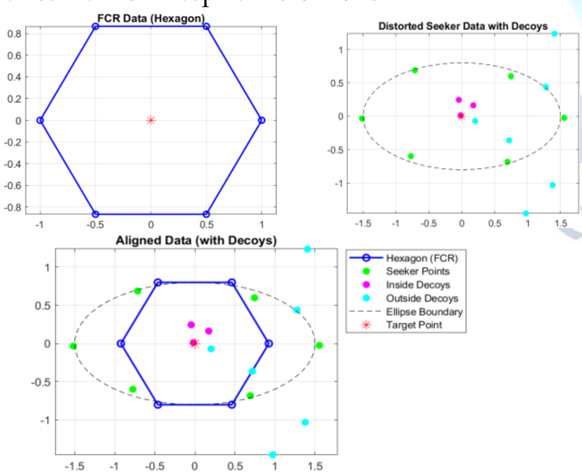

Fig 6.2 (c) Distortion Formations with Decoys

The addition of decoys near the formation makes it harder to spot the right ship.

In contrast to conventional methods, which suffer from significant performance drops, the GNN maintains strong matching efficiency even in this worst-case scenario by learning higher-order relational patterns and ignoring irrelevant noise and false targets.

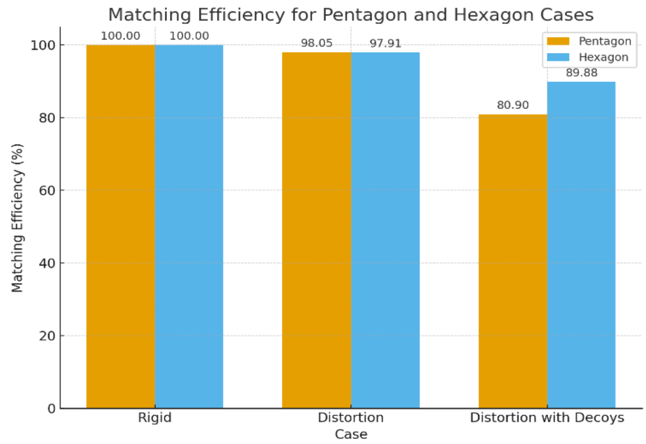

Fig: Comparison Graph for Pentagon and Hexagon Formations

In three distinct scenarios—Rigid, Distortion, and Distortion with Decoys- the bar graph contrasts the matching efficiency of a Pentagon and a hexagon. The algorithm operates flawlessly in the rigid formations with 100% efficiency in both shapes. Nevertheless, the efficiency progressively declines with the introduction of distortions and decoys. The Pentagon's efficiency declines more sharply, dropping to about 81% when decoys are present. Conversely, even in difficult circumstances, the Hexagon maintains a comparatively higher efficiency of roughly 90%. This demonstrates how the Hexagon alignment is more resilient, even though both shapes are impacted by distortions and decoys.

7. CONCLUSION

In this paper, we propose a target selection algorithm for Anti-Target Missile (ATM) systems based on Graph Neural Networks (GNNs) that uses fused measurements from seeker sensors and Fire Control Radar (FCR). In contrast to conventional methods, the suggested GNN method learns the relational and geometric structure of the ship formations modelled as elliptical Pentagons and Hexagons directly, avoiding explicit iterative alignment. The following significant findings were obtained from extensive MATLAB R2020a simulations:

- Robustness: The GNN maintained noticeably higher efficiency in distorted and decoy-rich environments and attained 100% matching efficiency in rigid formations.
- Generality: The GNN demonstrated its versatility to various geometrical configurations by generalising well across both Pentagon and Hexagon elliptical formations.
- Computational Advantage: The GNN offers a single-pass forward inference, which makes it more

appropriate for real-time target selection in missile guidance loops than conventional techniques that depend on iterative convergence.

- Defence Applicability: The suggested method shows that deep learning, more especially GNNs, can be implemented for next-generation defence systems that need to be resistant to geometric distortion and deceit.

Acknowledgement:

The author sincerely thanks Dr Lakshmi Bhavani K. for her invaluable advice, support, and encouragement during this research. Her expertise in structured learning and signal processing was extremely helpful in developing and refining the suggested Graphical Neural Network architecture.

The department's faculty and staff are also acknowledged by the author for their contributions, which included discussion, technical support, and resources that made this work possible.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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