Harnessing AI in Mindanao: Pathways for People-Centered Governance.

Dr. Sales G. Aribe Jr.
Bukidnon State University

Why we need AI in Governance?

- AI enables data-driven, anticipatory decision-making.
- Mindanao faces intersecting issues: health, governance, development.
- AI can transform reactive systems into proactive, predictive ones.

INTRODUCTION

HIV in the Philippines is NOW a ‘youth epidemic’.

ABS-CBN

HIV cases in PH rise by 500% among ages 15-25: DOH

Marilyn Cahatol, ABS-CBN News

Published Jun 03, 2025 09:44 AM PHT

Updated Jun 03, 2025 05:16 PM PHT

INTRODUCTION

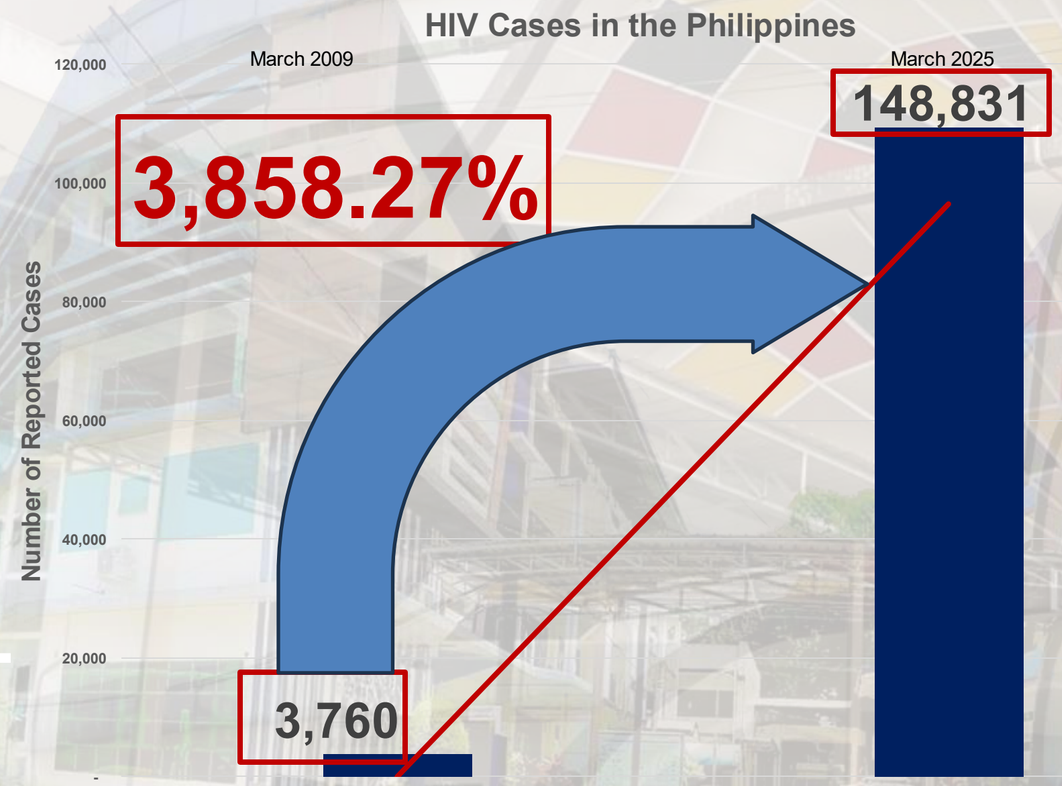
HIV Cases in Numbers (*Jan 1984 – Mar 2025*)

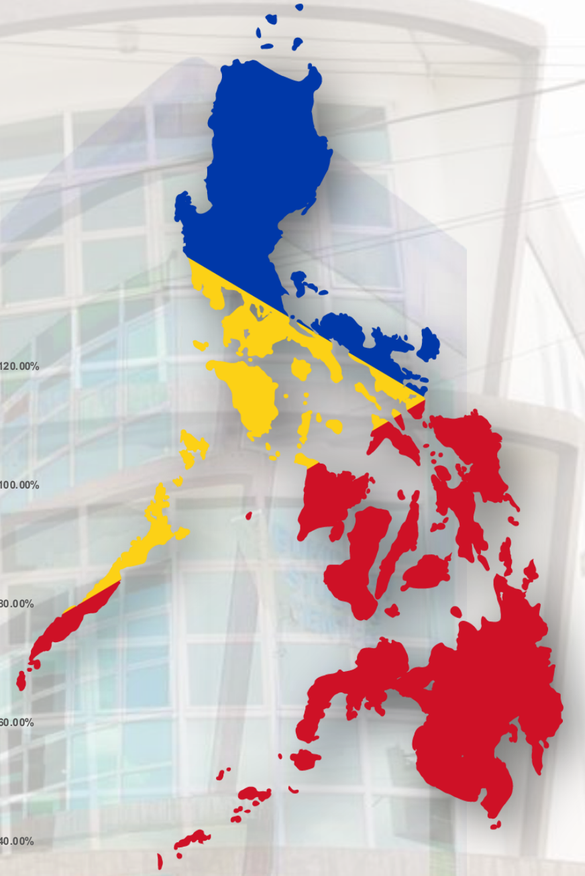
148,831
Total Cases

92,712
PLHIV enrolled in ART

9,221
Total Deaths

INTRODUCTION





Solution: **Forecasting using AI**

Why Forecasting Matters?

- Predict the trajectory of diseases
- Allocate budgets
- Mobilize resources
- Design preventive campaigns

BUKIDNON STATE UNIVERSITY
OFFICE OF THE VICE PRESIDENT FOR RESEARCH, EXTENSION AND INNOVATIONS
Research and Development Unit

Improved Forecasting Using a PSO-RDV Framework to Enhance Artificial Neural Network

International Journal of Engineering Trends and Technology (2024)

Methodology

ML Approaches to Predict HIV Cases

State-of-the Art Algorithm	References	Pros	Cons
Long Short-Term Memory (LSTM)	Greff et al., 2017	Good capacity in handling time-dependent datasets	Takes longer to train
Multilayer Perceptron (MLP)	Car et al., 2020	High generalization ability for long-term prediction	Requires dynamic modeling
Auto-Regressive Integrated Moving Average (ARIMA)	Alzahrani et al, 2020	Easy to fit and manage	Results should be interpreted with thriftiness
Susceptible-Exposed-Infectious-Recovered (SEIR)	Adiga et al., 2021	Simple; minimal number of parameters	Having two additional unknown parameters
Artificial Neural Network (ANN)	Ibrahim et al., 2022a; Rahmani-Rezaeieh et al., 2020; Song et al., 2019	Superior to earlier suggested forecasting models; efficient method with higher precision; most common among various disciplines	Poor predictive accuracy

Methodology

ANN DRAWBACKS

Poor Predictive Accuracy:

1. Training parameters of ANN are not enough to obtain reliable models
2. Additional parameter from any optimization method to update the weights and accelerate it towards its best location

APPROACH

Optimization Model by adding parameters

Methodology

Optimization Methods to Improve ANN

Swarm Intelligence Methods	References	Pros	Cons
Social-Spider Optimization (SSO)	Yeh et al., 2022	Provides a self-adjust model to reduce investors' effort in the trading market	Requires more related extended research
Whale Optimization Algorithm (WOA)	S. P. Singh & Tiwari, 2023	Remains highly secured compared to the existing techniques	Needs improvement in the FNR values
Multi-Objective Grey Wolf Optimizer (MOGWO)	Mushavarati et al., 2022	Provides optimal condition	Should focus on increasing efficiency to improve performance
Marine Predators Algorithm (MPA)	Alawsi et al., 2022	Improve data quality	The performance of CPSOCGSA-ANN is better than MPA-ANN
Particle Swarm Optimization (PSO)	Gad, 2022; Shami et al., 2023	Popular choice among academics because of good performance; Efficient use of memory and easy implementation; Effective in achieving the global minimum with less iterations	Poor convergence performance

Methodology

PSO DRAWBACKS

Poor convergence:

1. Absence of a parameter that regulate the movement of the particle velocity

2. Fails to discover the global optimum solution and converges at a very slow speed towards the global solution point

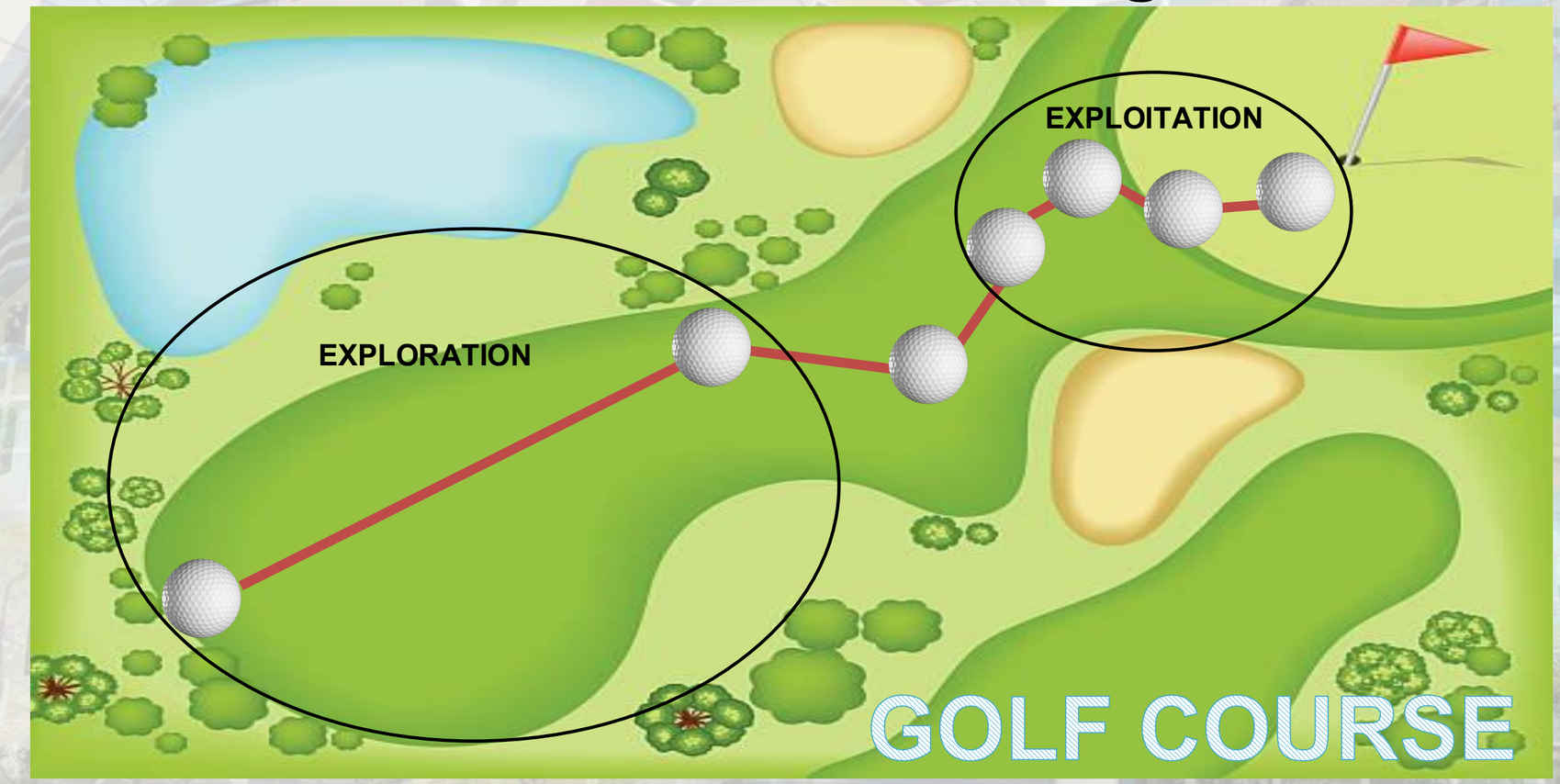
APPROACH (RDV)

➡ Integration of RDV parameters
(**α**, **α**_dump, **δ**)

➡ Determine the optimal combination of RDV IW control parameters with least position error
(**α** [0.1, 1.0], **α**_dump [0.5, 1.0])

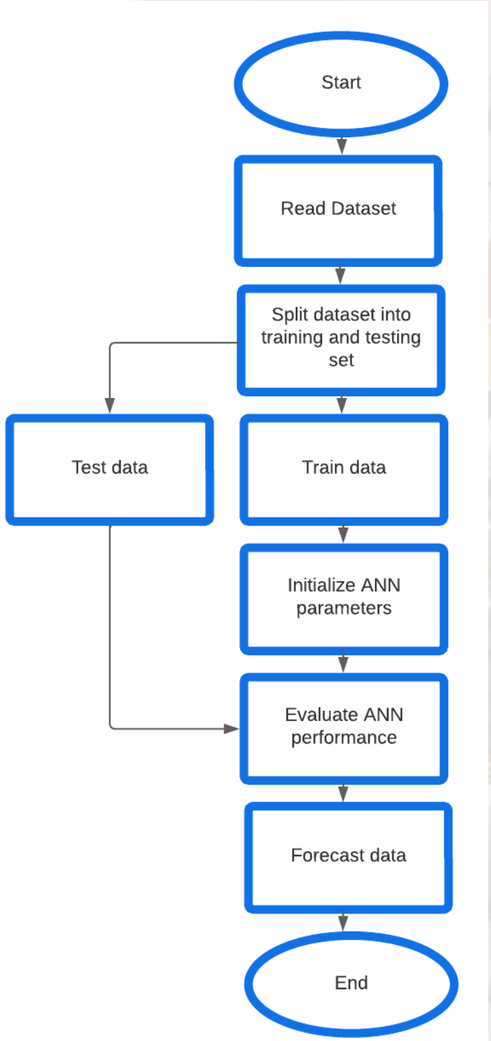
Methodology

What is RANDOM DESCENDING VELOCITY Inertia Weight?



Framework

ANN



$$S = w_1x_1 + w_2x_2 + \cdots \text{next}, = \sum w_ix_i \quad (1)$$

$$S = \sum_{i=1}^{n}(w_ix_i - \theta) \quad (2)$$

$$S = f(x) = x \quad (3)$$

$$\delta = b - s = b - x \quad (4)$$

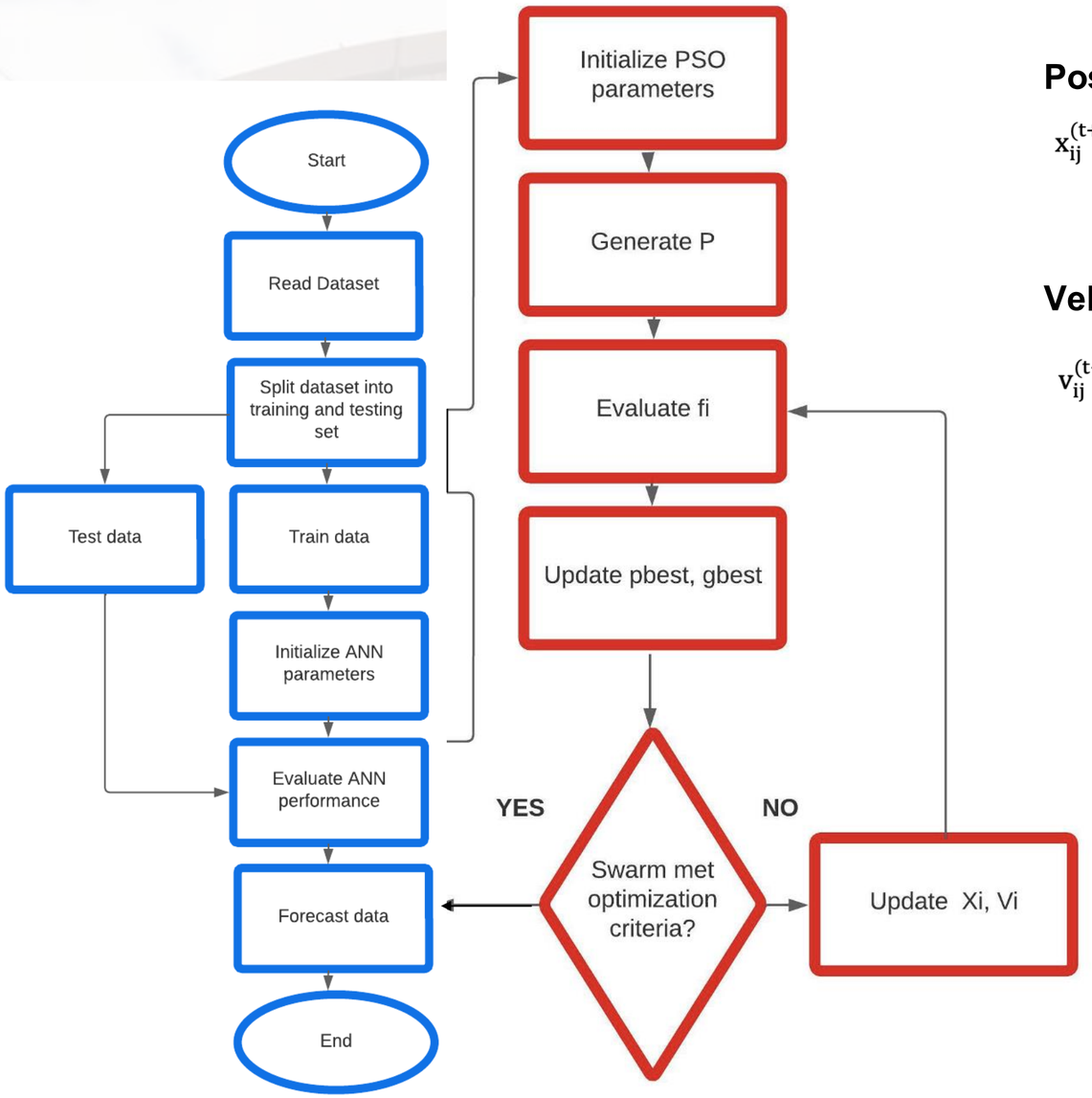
$$f(x) = 1, x > 0 \quad (5)$$

$$f(x) = 0, x \leq 0 \quad (6)$$

$$yt = f(y(t-1) + y(t-2) + y(t-3) + y(t-m)) \quad (7)$$

Framework

ANN-PSO



Position (X_i)

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \quad (8)$$

Velocity (V_i)

$$v_{ij}^{(t+1)} = v_{ij}^{(t)} + c_1 r_1 \left(x_{ij}^{p(t)} - x_{ij}^{(t)}\right) + c_2 r_2 \left(x_j^{g(t)} - x_{ij}^{(t)}\right) \quad (9)$$

ANN-PSO-RDV IW

alpha (α), alpha_dump (α_dump)

$$\alpha = \alpha * \text{alpha_dump} \quad (11)$$

$$v_{ij}^{(t+1)} = wv_{ij}^{(t)} + c_1 r_1 \left(x_{ij}^{p(t)} - x_{ij}^{(t)}\right) + c_2 r_2 \left(x_j^{g(t)} - x_{ij}^{(t)}\right) \quad (12)$$

GENERAL OBJECTIVES

This study aims to integrate the **RDV IW** technique to improve the **accuracy** and **convergence** performance of **ANN-PSO** in forecasting the number of HIV/AIDS cases in the Philippines.

RESULT

alpha, alpha_dump = [0.3, 0.95] → bad outcome

1
2
3

Claim 1	The convergence performance is affected by the optimal combination of RDV IW control parameters.
Specific Objective 1	Determine the optimal combination of the RDV IW control parameters with least position error in terms of: a. alpha b. alpha_dump
Materials and Methods	Generate 100 combination of RDV IW control parameters with values of alpha [0.1, 1.0] and alpha_dump [0.5, 1.0] Determine the least position error.
Measures	**Position Error** $PE = \sqrt{(x^2 - x^1) + (y^2 - y^1) + (z^2 - z^1)}$

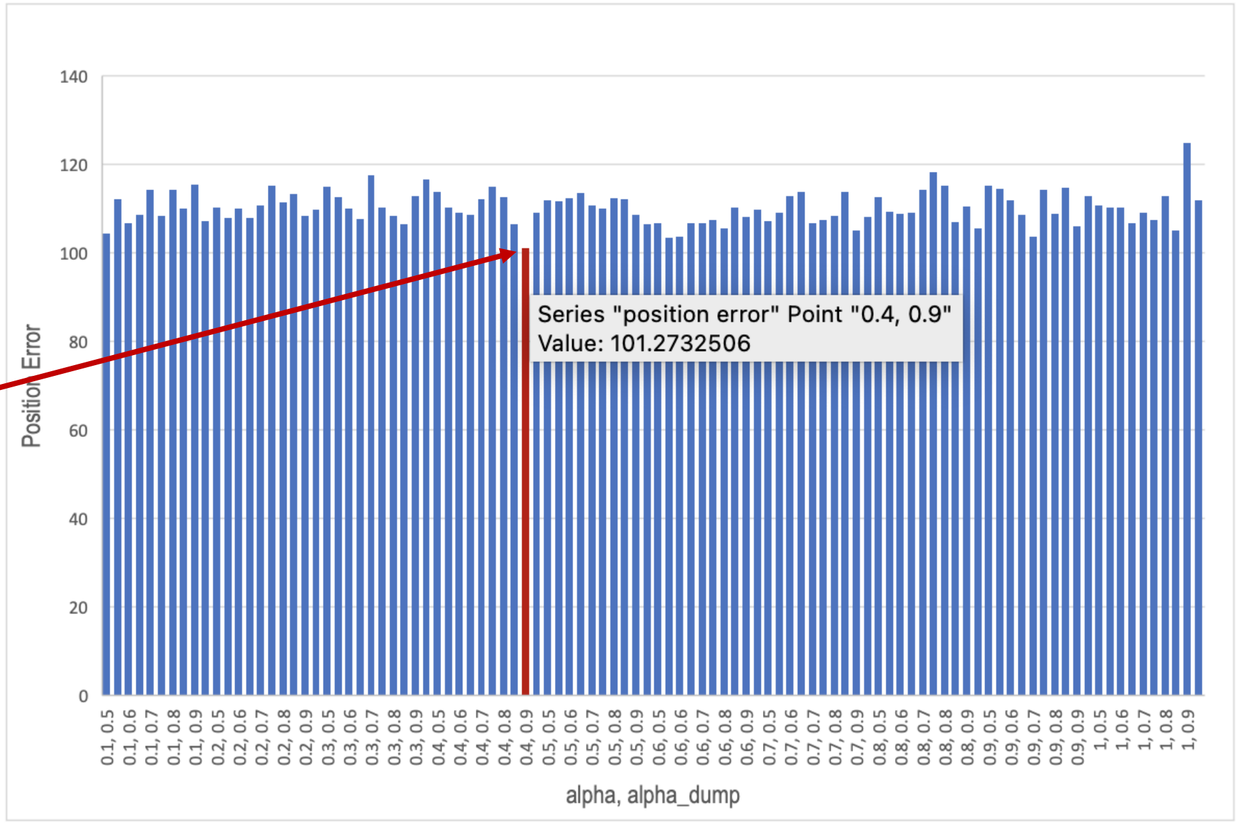
Specific Objective 1:

Determine the optimal combination of the RDV IW control parameters with least position error in terms of:

a. alpha
b. alpha_dump

1
2
3

alpha	alpha_dump	Position Error
0.1	0.5	104.58159
0.1	0.55	112.226553
0.2	0.5	110.38875
0.2	0.55	108.158729
0.3	0.5	115.012678
0.3	**0.95**	**116.854028**
0.4	0.5	113.982132
0.4	0.55	110.453717
0.4	**0.9**	**101.273251**
0.5	0.5	111.951134
0.5	0.55	111.844121
0.6	0.5	106.844099
0.6	0.55	103.632794
0.7	0.5	107.232972
0.7	0.55	109.182344
0.8	0.5	112.712593
0.8	0.55	109.426907
0.9	0.5	115.285845
0.9	0.55	114.545124
1.0	**0.9**	**124.92442**



1
2
3

Claim 2	ANN-PSO integrated with RDW IW technique provides better convergence.
Specific Objective 2	Determine the improvement in the convergence performance of ANN-PSO with the integration of RDV IW in terms of: a. Position Error b. Computational Time c. Number of Iterations
Materials and Methods	HIV dataset Perform 20 independent runs RDV IW Parameters Find the min, max, and ave from the evaluation measures

Measures	**Position Error**	**Number of Iterations**	**Computational Time**	**Improvement (%)**
	$PE = \sqrt{(x^2 - x^1) + (y^2 - y^1) + (z^2 - z^1)}$			$\text{Improvement} = \left(\frac{\text{This study} - (\text{ANN} - \text{PSO})}{\text{This Study}}\right) * 100$

Specific Objective 2: Determine the improvement in the convergence performance of ANN-PSO with the integration of RDV IW in terms of:

a. Position Error
b. Computational Time
c. Number of Iterations

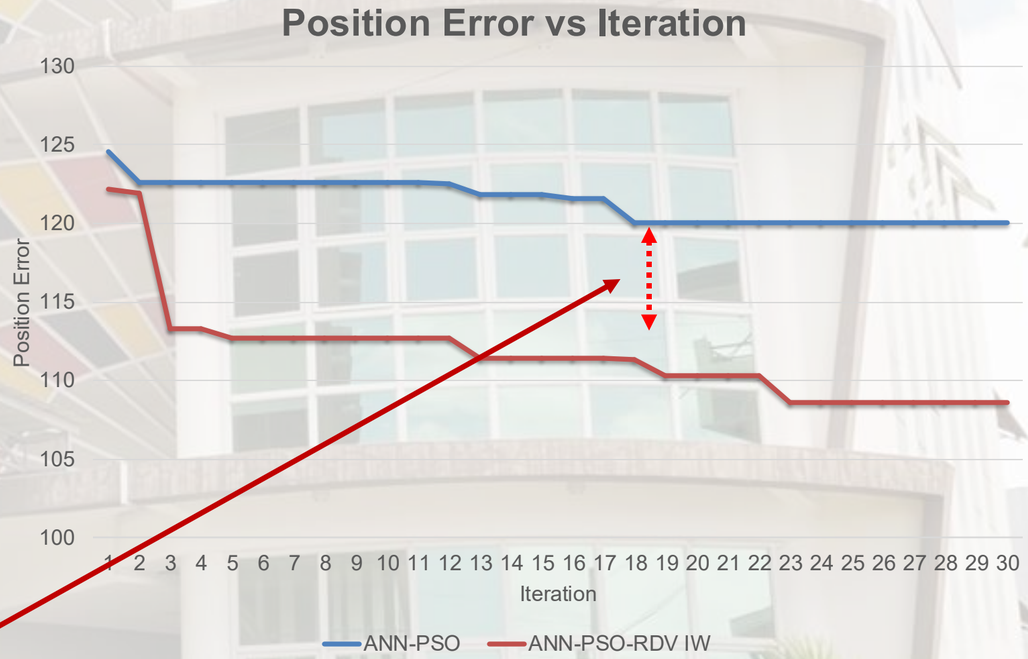
1
2
3

Position Error

Condition	This study	ANN-PSO
Min	**101.2732506**	107.71067
Max	**111.46789**	120.07746
Average	**108.99974**	110.93828

Improvement in MIN (This study vs ANN-PSO)

6.36%



Specific Objective 2: Determine the improvement in the convergence performance of ANN-PSO with the integration of RDV IW in terms of:

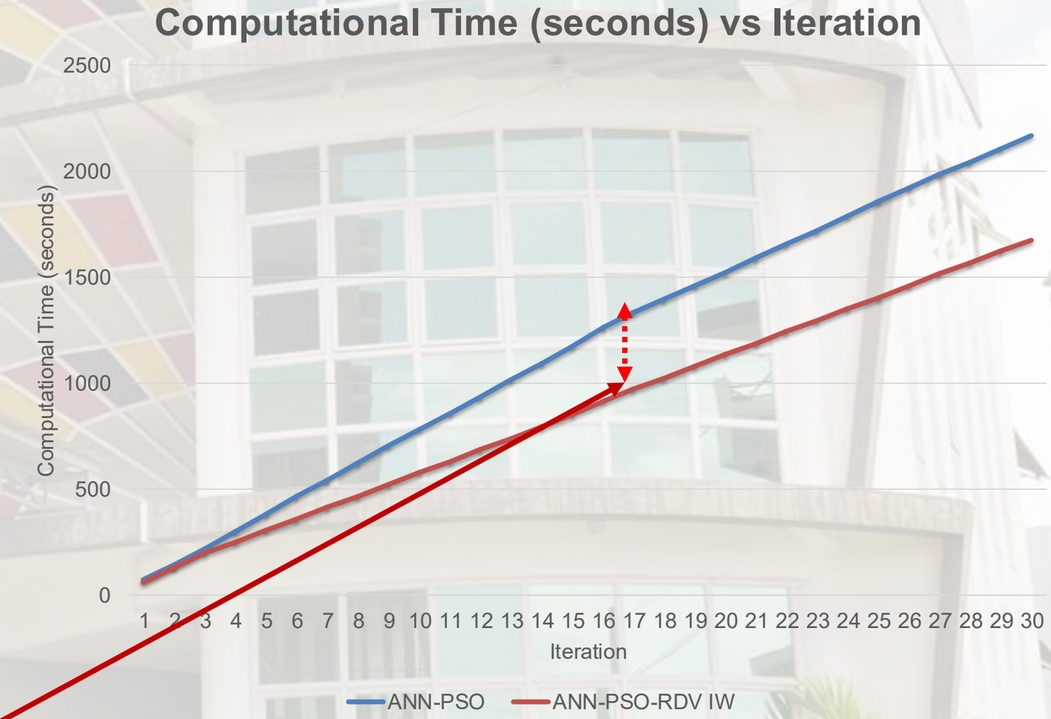
a. Position Error
b. Computational Time
c. Number of Iterations

1
2
3

Condition	Computational Time (in seconds)	
	This study	ANN-PSO
Min	**210.01812**	234.68989
Max	**1,678.90319**	2,169.69820
Average	**511.49391**	827.92385

Improvement in MIN (This study vs ANN-PSO)

11.75%



Specific Objective 2:

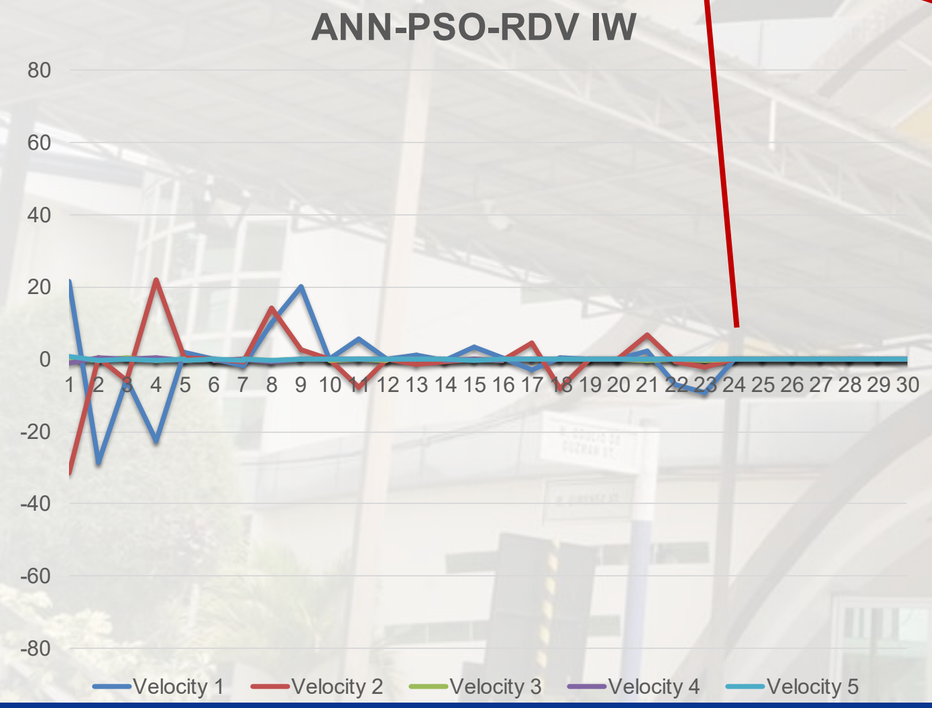
Determine the improvement in the convergence performance of ANN-PSO with the integration of RDV IW in terms of:

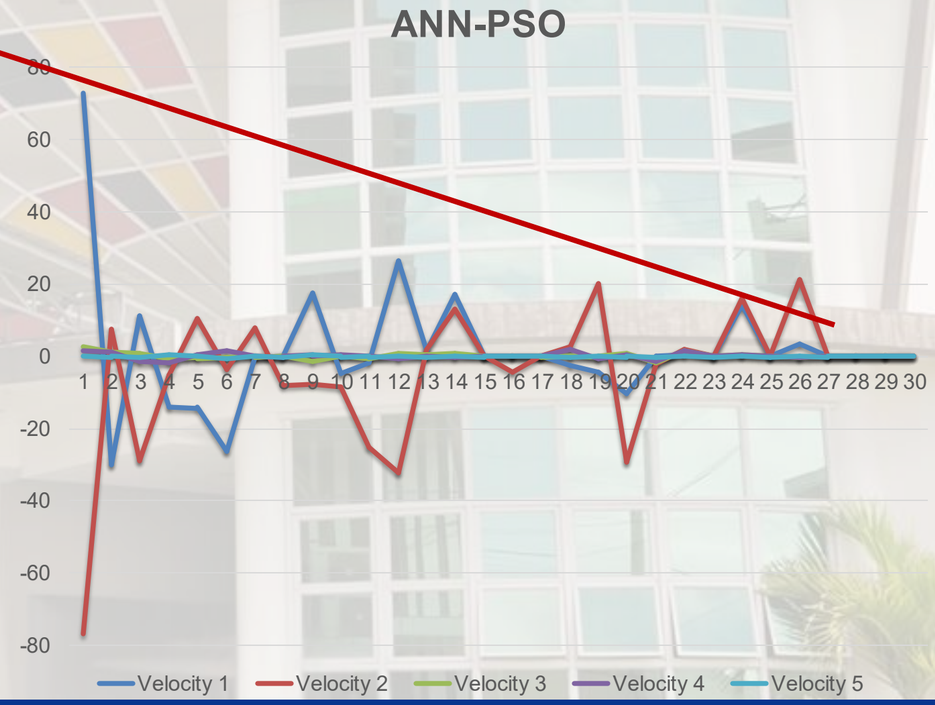
a. Position Error
b. Computational Time
c. Number of Iterations

Algorithm	Number of Iterations
This Study	24
ANN-PSO	27

12.50% Improvement

1
2
3





Claim 3	ANN-PSO integrated with RDW IW technique provides better accuracy performance.
Specific Objective 3	Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of: a. NRMSE b. MAE c. MAPE d. WAPE and e. R^2
Materials and Methods	HIV dataset Perform 20 independent runs PSO Parameters Compute p-values for the significant improvement
Measures	$\mathbf{NRMSE} = \frac{\sum(S_i - O_i)^2}{\sum O_i^2}$ $\mathbf{MAE} = \frac{1}{N}\sum_{i=1}^{N_s}\lvert P_{yi} - Y_i\rvert$ $\mathbf{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\lvert\frac{P_{yi} - Y_i}{YP_i}\rvert$ $\mathbf{WAPE} = \frac{\sum_{i=1}^{N}\lvert y_i - p_i\rvert}{\sum_{i=1}^{N}\lvert y_i\rvert}$ $\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n}(Y_i - P_{yi})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2}$ $p - value < 0.05$

1
2
3

Simulation Results

Specific Objective 3: Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of:

a. NRMSE
b. MAE
c. MAPE
d. WAPE and
e. R^2

1
2
3

NRMSE

Condition	This study	ANN-PSO	ANN
Min	**0.19131**	0.19346	0.22504
Max	**0.20021**	0.21567	0.28111
Average	**0.19578**	0.19926	0.25214

0.04889174

p-value

(This study vs ANN-PSO)

Simulation Results

Specific Objective 3: Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of:

a. NRMSE
b. MAE
c. MAPE
d. WAPE and
e. R^2

1
2
3

MAE

Condition	This study	ANN-PSO	ANN
Min	**78.57648**	79.66181	98.40206
Max	**84.16433**	90.36778	123.7563
Average	**82.12563**	83.09121	110.42677

0.02829063

p-value

(This study vs ANN-PSO)

Simulation Results

Specific Objective 3: Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of:

a. NRMSE
b. MAE
c. MAPE
d. WAPE and
e. R^2

1
2
3

MAPE

Condition	This study	ANN-PSO	ANN
Min	**0.08451**	0.08532	0.10298
Max	**0.08948**	0.09624	0.12610
Average	**0.08788**	0.08918	0.11401

0.02226053

p-value

(This study vs ANN-PSO)

Simulation Results

Specific Objective 3: Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of:

a. NRMSE
b. MAE
c. MAPE
d. WAPE and
e. R^2

1
2
3

WAPE

Condition	This study	ANN-PSO	ANN
Min	**0.08270**	0.08384	0.10138
Max	**0.08858**	0.09511	0.12750
Average	**0.08643**	0.08745	0.11377

0.01701545

p-value

(This study vs ANN-PSO)

Simulation Results

Specific Objective 3: Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of:

a. NRMSE
b. MAE
c. MAPE
d. WAPE and
e. R^2

1
2
3

Condition	R^2		
	This study	**ANN-PSO**	**ANN**
Min	**0.73045**	0.62302	0.14312
Max	**0.78865**	0.67482	0.18271
Average	**0.75963**	0.63621	0.15892

0.00000021

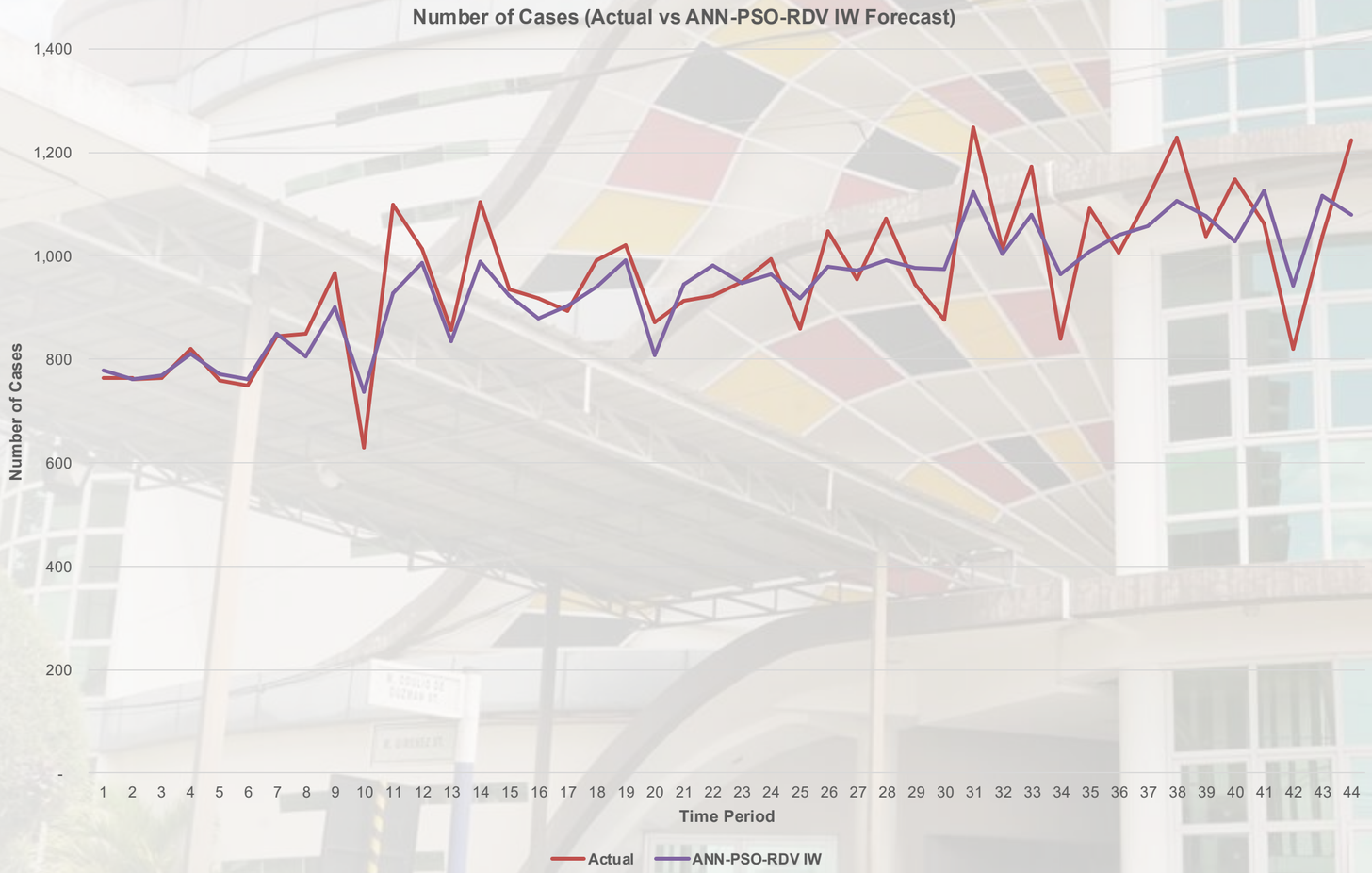
p-value

(This study vs ANN-PSO)

Results

1
2
3

Forecast vs actual



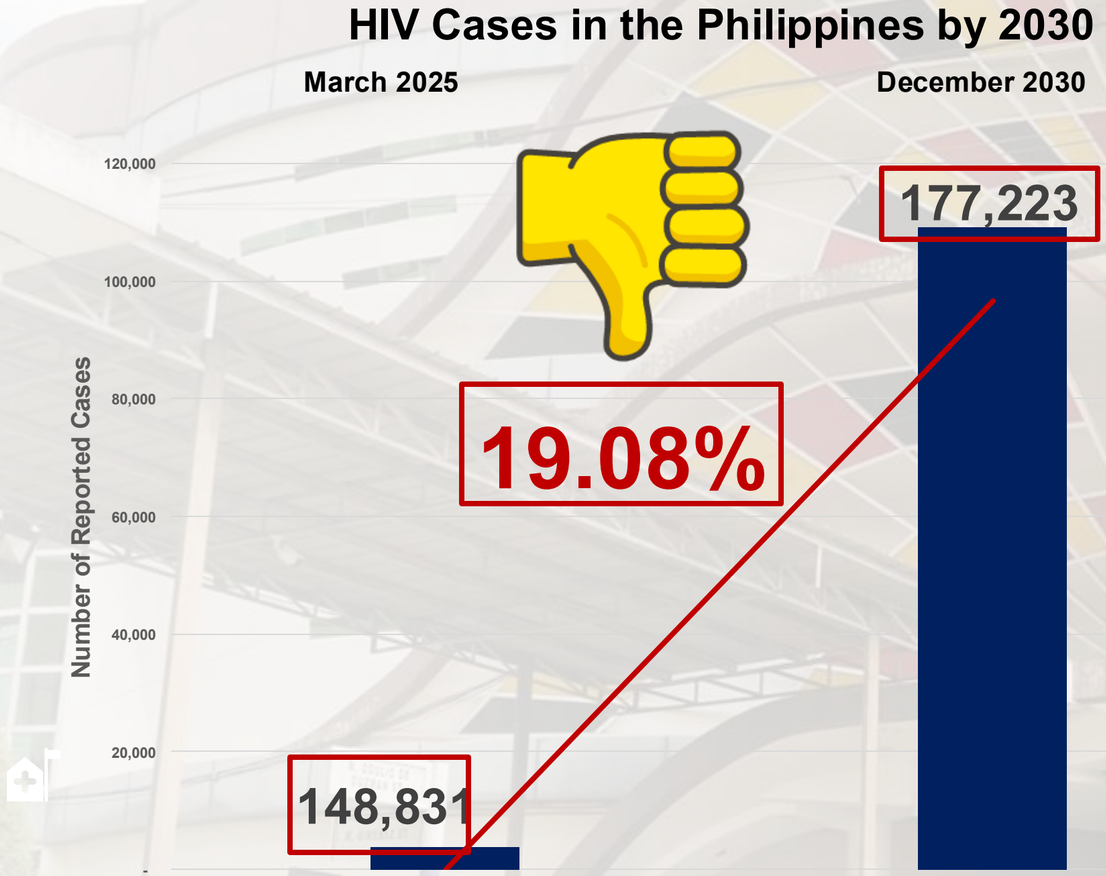
Conclusions

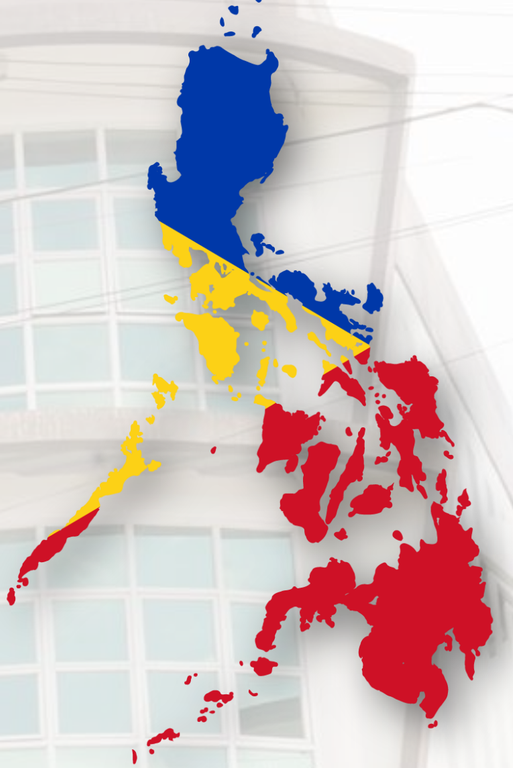
Specific Objective		Conclusion
1. Determine the optimal combination of the RDV IW control parameters with least position error in terms of: a. alpha and b. alpha_dump		1. The optimal combination of RDV IW parameters which generates least position error is: a. alpha = 0.4 and b. alpha_dump = 0.9
2. Determine the improvement in the convergence performance of ANN-PSO with the integration of RDV IW in terms of: a. Position Error b. Computational Time and c. Number of Iterations		2. The ANN-PSO integrated with RDV IW provides better convergence performance compared to the old model, as shown by a. 6.36% improvement in position error b. 11.75% improvement in computational time and c. 12.50% improvement in the number of iterations
3. Determine the significant improvement in the accuracy performance of ANN-PSO with the integration of RDV IW based on the computed p-values of: a. NRMSE b. MAE c. MAPE d. WAPE and e. R^2		3. The ANN-PSO integrated with RDV IW produced significant improvement in the accuracy performance, as shown by a. a p-value of 0.04889174 in NRMSE b. a p-value of 0.02829063 in MAE c. a p-value of 0.02226053 in MAPE d. a p-value of 0.01701545 in WAPE and e. a p-value of 0.00000021 in R^2 ***which is less than the standard p-value of <u>0.05</u> in the significance level.***

Conclusions

General Objective	General Conclusion
This study aims to integrate the RDV IW technique to improve the accuracy and convergence performance of ANN-PSO in forecasting the number of HIV/AIDS cases in the Philippines.	The conclusions above proved that the integration of RDV IW technique using an optimal combination [0.4, 0.9] provides faster convergence rate and better predictive accuracy to ANN-PSO in forecasting the number of HIV/AIDS cases in the Philippines.

FORECASTING





POLICY PROPOSAL

- AI-Driven Health Forecasting and Decision Support System
  1. Integration of AI Forecasting Models
  2. Creation of a Mindanao AI for Public Health Data Center
  3. Interoperable Data Systems.
  4. AI Literacy and Training for Policymakers
  5. Ethical and Responsible AI Framework
- Curriculum Integration

Why It Matters for Mindanao?

One Mindanao Data Ecosystem

- LGUs can identify risk areas before outbreaks spread.
- DOH can anticipate medicine demand and budget accordingly.
- Policymakers can justify interventions with predictive evidence.

VISION

National AI Strategy Project 2028

DOST Philippines · Follow
4h ·

DOST in the NEWS: The Department of Science and Technology (DOST) is aiming to establish an artificial intelligence (AI)-powered Philippines by 2028 as part of its National AI Strategy (NAIS PH) project.

#OneDOST4U
#SolutionsAndOpportunitiesforAll

DOST eyes AI-powered PH by 2028

SOURCE: PHILIPPINE NEWS AGENCY

DEPARTMENT OF SCIENCE AND TECHNOLOGY
OneDOST4U: Solutions and Opportunities for All

CALL TO ACTION

"AI in governance is not about replacing people—it's about empowering them with foresight."