# **GNSS Geodetic Velocity Prediction Using Deep Neural Network: A Case Study of Cairo Area, Egypt**

Alshimaa Y. Abo Gharbia<sup>1</sup>, Moatamad R. Hassan<sup>2</sup>, Mohamed Saleh<sup>1</sup>, Ahmed Gomaa<sup>1</sup>, Ashraf Elkutb Mousa<sup>1</sup>, and

Ibrahim Atiatallah Abbas<sup>3</sup>

<sup>1</sup> Department of Geodynamics, National Research Institute of Astronomy and Geophysics (NRIAG), El-Marsad St., 11722 Helwan, Egypt.

<sup>2</sup> Department of Mathematics and Computer Science, Faculty of Science, Aswan University, Aswan 81528, Egypt.

<sup>3</sup> Department of Mathematics, Faculty of Science, Sohag University, Sohag 82511, Egypt.

E-mail: <u>alshimaayousri@nriag.sci.eg</u>

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**Abstract:** Estimating and studying global navigation satellite system (GNSS) velocities play an essential role in understanding the deformation and motion of the crust. Thus, in this research, we employ a deep neural network (DNN) to estimate horizontal velocities at certain places using GNSS data. Data on crustal deformation are obtained by using Global Positioning System (GPS) techniques. The exact locations of the three stations were obtained by recording, analyzing, and adjusting permanent GPS measurements. Moreover, 70% of the GNSS velocities from stations in the Cairo region and International GNSS Service (IGS) stations were used in the analysis to train the proposed DNN model, with the remaining 30% set aside for testing. The horizontal velocity components (east and north) were estimated using the DNN model. The highest differences between the velocities obtained by the DNN model and the reference velocities were 0.0004 mm. These findings highlight the ability of the DNN model to provide precise GNSS velocity estimates for geodetic applications.

Keywords: GPS; DNN; Cairo.

#### **1. Introduction**

Global plate motion models (e.g., NUVEL-1 and NUVEL-1A) are used to understand tectonic structures and large-scale crustal movements. Subsequently, GPS data were utilized for determining geodetic velocities [1, 2]. The development of GPS technology made it possible to use GPS measurements to monitor crustal motions directly. Researchers can now gain a more detailed understanding of crustal motion and deformation processes by examining GNSS velocities. Geodetic velocities are usually computed using traditional interpolation techniques, such as Kriging models, in areas lacking GPS stations. Artificial intelligence (AI) techniques such as artificial neural networks (ANNs), deep learning (DL), and machine learning (ML) have acquired popularity as substitutes in this sector of geosciences lately [3-8]. This study assesses the effectiveness of these methods in estimating horizontal velocities by employing DNN algorithms specifically.

The DNN model offers an effective tool for forecasting GNSS station velocities while considering geographical variables. These models provide crucial information for displacement analysis and geodynamic research. The GNSS, a constellation of satellites, provides global positioning and navigation services. For this study, three geodetic stations were used in the Cairo area from 2022 to April 2023. Utilizing the DNN to calculate the east and north velocities for each station until April 2023 provides the ability to estimate east and north velocities till September 2023.

#### 1.1 Study Area

The study area is centered in Cairo, the capital city of Egypt, located in the northeastern part of the country. Cairo's geographic coordinates are approximately 30.0444° N latitude and 31.2357° E longitude. The city is situated on the eastern bank of the Nile River and covers an extensive area that includes a variety of geological and urban landscapes.

Cairo lies within the tectonically active region influenced by the Nubian, Arabian, and Eurasian plates. The geological setting of Cairo is primarily characterized by sedimentary rock formations, including limestone, sandstone, and shale, which are part of the broader Nile Delta region. This region is known for its complex geological history, which both tectonic and sedimentary processes have shaped. A network of geodetic GPS stations has been established throughout the Cairo metropolitan area to monitor and analyze crustal movement. These stations provide precise and continuous measurements of the Earth's surface, allowing for the detection of minute movements and deformations. The selected GPS stations are strategically distributed across various districts, including Downtown Cairo and the Mokattam Hills, to ensure comprehensive coverage of the study area. The GPS data collected from these stations are analyzed to understand the crustal dynamics, including the rates and directions of ground movement. The study aims to provide valuable insights into the tectonic behavior of the region, contributing to the understanding of seismic hazards and the potential for future geological events. The findings from this

research are expected to enhance the knowledge of crustal movements in Cairo and support the development of mitigation strategies to reduce the impact of tectonic activity on the urban infrastructure.

#### 1.3 GPS Data

Fig. 1 illustrates the three geodetic GPS stations used in the Cairo area from 2022 to April 2023. The GPS stations' names and coordinates are listed in Table 1.



Fig. 1. Location map of the study area (red rectangular), Cairo area, Egypt.

Table 1. Geographic location of	the Cairo geodetic stations with
reference to WGS 1984.	

Station	Latitude	Longitude	Height (m)
ADIS	9° 2' 6.49"N	38° 45' 58.69" E	2439.1
DRAG	31° 35' 35.52	35° 23' 31.45" E	31.8
	" N		
KATA	29°55′39″N	31°49′45.12″E	495.596
IISC	13° 1' 16.2" N	77° 34' 13.35" E	843.71
MATE	40° 38' 56.87"	16° 42' 16.05" E	535.6
	Ν		
MSLT	29°30'49.68"	30°53′19.32″E	5.102
	Ν		
NICO	35° 8' 27.56"	33° 23' 47.22" E	190.1
	Ν		
NOT1	36° 52' 34" N	14° 59' 23.31" E	126.2
PHLW	29°51′41.4″N	31°20′36.24″E	148.749
RABT	33° 59' 53.17"	-6° 51' 15.44" E	90.1
	Ν		
YEPE	40° 31' 29.63"	-3° 5' 19.07" E	972.8
	Ν		
ZIMM	46° 52' 37.54"	7° 27' 55" E	956.4
	Ν		

#### 2. Materials and Methods

#### 2.1. GPS Measurements

In the Cairo region, three GPS stations were used from 2022 to April 2023. The measurements are conducted with field equipment consisting of receiver units and auxiliary devices like

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batteries, a compass, and other accessories. Accurate baseline readings are obtained using dual-frequency geodetic receivers. At every station, the minimum elevation mask angle is 15 degrees, and the data sampling interval is set to 30 seconds. To enhance the datum definition and precision of the three stations' GPS results, 10 permanent stations from the International GNSS Service (IGS) dataset (ADIS, DRAG, IISC, MAL2, MATE, NICO, NOT1, RABT, ZIMM, and YEBE) are also examined, as well as the three stations GPS observations. Furthermore, in Fig. 2, IGS stations (International Terrestrial Reference Frame (ITRF2014)) [9] are arranged sensibly around the study area. IGS accurate satellite orbits are used to find the daily coordinate solution. Following a traditional processing scheme and processing strategy, GPS data are processed using Bernese software V.5.2 [10], as follows:

1) ITRF2014 reference frame.

2) NNR-NUVEL-1A plate motion model for non-ITRF stations3) The application of IGS products from 2022 to April 20234) Baselines that are automatically created using the MAX-OBS technique.

5)  $15^{\circ}$  is the elevation cut-off angle.

6) Linear ionosphere-free (LIF) combination

7) Dry Niell as a troposphere model with (the Vienna mapping function) global mapping function

The double-differenced observation technique is used to find daily minimum-constrained solutions for the processing strategy. Precise IGS orbits, earth orientation parameters, and an absolute antenna phase center are used in daily data processing. It has proven possible to resolve integer phase ambiguities using the SIGMA and QIF (quasi-ionosphere-free) techniques.



**Fig. 2.** Distribution of International GNSS Service (IGS) stations.

#### 2.2. Deep Neural Network Model:

This study aims to analyze crustal movements in Cairo using geodetic GPS station data. The methodology consists of several key steps, including data acquisition, preprocessing, model development, training, and evaluation. The dataset was split into training and testing sets: 70% of the data for training and 30% for testing. the optimal hyperparameters for the neural

network model. Various configurations of the model were evaluated by iteratively altering the key parameters, including the number of neurons in the first and second hidden layers (ranging from 32 to 128 and 16 to 64, respectively), activation functions (ReLU, sigmoid, and tanh), and dropout rates (0.0, 0.2, and 0.4). The model was trained with 300 epochs and a batch size of 10. Its performance was measured using mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination ( $R^2$ ). The results of this analysis, stored in a structured DataFrame and exported for documentation, allowed for a comprehensive evaluation of the model's behavior under different hyperparameter settings, aiding in the selection of an optimal configuration. The model was compiled using the Adam optimizer and MSE as the loss function.

The model was trained on the training data for each target variable in the dataset. For each target variable, a separate model was created and trained for 300 epochs with a batch size of 10. The training process involved fitting the model to the input features and target values. The model's performance was evaluated using the testing data. Predictions were generated for each target variable, and the accuracy of the predictions was determined using MAE, RMSE, and R<sup>2</sup> score. Furthermore, the results were visualized using Matplotlib to compare the training data, testing data, and predictions.

In this study, the random forest algorithm was utilized to predict the velocities of geodetic stations based on Global Positioning System (GPS) data, and its results were compared to those of the deep neural network (DNN). Although random forest demonstrated its ability to handle high-dimensional data and nonlinear relationships, its performance was evaluated using metrics such as root mean squared error (RMSE) and the coefficient of determination ( $R^2$ ). However, DNN exhibited significantly better results, showcasing its superior capability in extracting complex patterns from the data. These results highlight the advantage of employing DNNs for predictive tasks in geodetic analysis.

In this study, Monte Carlo simulation was applied to quantify the uncertainty in predictions made by the model. The simulation involved generating multiple predictions by introducing stochastic behavior during prediction. Specifically, randomness was maintained by enabling training mode in the model, keeping dropout layers active during inference. For each simulation, predictions were recorded, and the mean prediction and standard deviation, representing uncertainty, were calculated. These metrics allowed the assessment of the model's reliability under uncertain conditions. The true values were plotted alongside the mean predictions, and the uncertainty was visualized as a shaded confidence region around the predictions. The results highlighted that the true values consistently fell within the uncertainty bounds, demonstrating the robustness of the model as shown in Figs. 7 and 8.

## 3. Results and Discussion

We calculated the north and the east velocities for all study

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stations until April 2023, and the results are displayed in Table. 2. By applying DNN algorithms, we predicted north velocities and east velocities until September 2023, as shown in Table 2. Notably, the computed velocity and the velocity estimations obtained by DNN methods are consistent. Using the DNN algorithms, we estimated the standard deviations of the velocity values, as shown in Table. 2. The actual data and DNN predictions for the east and north velocities are demonstrated in Figs. 3, 4, 5, and 6. As illustrated, the variation between the observations and the forecasts are in the normal distribution. **Table 2**. The geodetic stations, GNSS geodetic velocities, and velocities predictions(mm/yr) from DNN of Cairo stations and IGS stations.

Stati on	GNSS geodetic velocity (mm/yr)		Velocity predictions from DNN (mm/yr)					
	VE	σΕ	VN	σΝ	VE	σΕ	VN	σΝ
ADI	18.	2.1	24.	2.7	18.62	2.1	24.71	2.7
S	63	9	72	9	98	9	98	9
DRA	24.	2.2	27.	2.4	24.55	2.2	27.66	2.4
G	56	4	67	2.4	95	4	94	2.4
шас	35.	1.3	35.	2.5	35.65	1.3	35.16	2.5
lise	66	6	17	8	96	6	96	8
KAT	25.	2.1	19.	2.0	25.51	2.1	19.79	2.0
Α	52	5	8	1	97	5	98	1
MA	24.	1.4	18.	2.9	24.57	1.4	18.40	2.9
TE	58	1	41	1	98	1	98	1
MSL	23.	2.3	18.	3.2	23.20	2.3	18.73	3.2
Т	21	3	74	2	98	3	98	2
NIC	16.	2.2	16.	2.6	16.51	2.2	16.89	2.6
0	51	8	89	6	00	8	00	6
NOT	23.	1.7	17.	2.3	23.26	1.7	17.39	2.3
1	27	8	4	5	98	8	98	5
PHL	24.	2.0	19.	2.6	24.30	2.0	19.31	2.6
W	31	1	32	2	98	1	98	2
RAB	18.	2.0	17.	2.3	18.57	2.0	17.60	2.3
Т	58	7	61	5	98	7	98	5
YEP	21.	2.0	16.	2.7	21.30	2.0	15.99	2.7
E	31	7	00	1	98	7	98	1
ZIM	21.	2.1	14.	2.7	21.59	2.1	14.43	2.7
Μ	60	3	44	5	98	3	99	5

**Table 3**. The geodetic stations, GNSS geodetic velocities, and velocities predictions(mm/yr) from RF of Cairo stations and IGS stations.

Statio	GNSS geodetic velocity (mm/yr)			Velocity predictions from RF (mm/yr)			ons r)	
11	VE	σΕ	VN	σΝ	VE	σΕ	VN	σΝ
ADIS	18.6 3	2.1 9	24.7 2	2.7 9	18.6 2	2.1 8	24.7 1	2.7 8
DRA	24.5	2.2	27.6	24	23.1	2.1	27.6	2.3
G	6	4	7	2.4	9	1	4	9
	35.6	1.3	35.1	2.5	35.6	1.3	35.1	2.5
IISC	6	6	7	8	5	5	4	7

KAT	25.5	2.1	10.0	2.0	25.5	2.1	19.7	2.0
Α	2	5	19.8	1	1	4	9	0
MAT	24.5	1.4	18.4	2.9	24.5	1.4	18.4	2.9
E	8	1	1	1	7	0	0	0
MSL	23.2	2.3	18.7	3.2	23.2	2.3	18.7	3.2
Т	1	3	4	2	0	2	1	1
NIC	16.5	2.2	16.8	2.6	16.4	2.2	16.7	2.6
0	1	8	9	6	7	7	5	3
NOT	23.2	1.7	174	2.3	22.9	1.7	17.3	2.3
1	7	8	17.4	5	3	5	8	4
PHL	24.3	2.0	19.3	2.6	24.0	1.9	19.2	2.6
W	1	1	2	2	4	8	8	1
RAB	18.5	2.0	17.6	2.3	18.5	2.0	17.5	2.3
Т	8	7	1	5	1	6	6	4
YEP	21.3	2.0	16.0	2.7	21.3	2.0	15.5	2.6
E	1	7	0	1	0	6	5	3
ZIM	21.6	2.1	14.4	2.7	21.5	2.1	14.3	2.7
Μ	0	3	4	5	7	2	3	2

Tables **4**, **5**, **6**, and **7** list MAE, R<sup>2</sup>, and RMSE values for north velocities and east velocities for each station based on the DNN and RF models.

**Table 4.** MAE, RMSE, and  $R^2$  of east GNSS velocities predictions from DNN for all stations.

Station	MAE	RMSE	$\mathbb{R}^2$
ADIS	3.46E-06	1.60E-11	0.99999
DRAG	1.17E-05	1.36E-10	0.99998
IISC	7.20E-07	7.57E-13	0.99999
MATE	1.45E-07	2.10E-14	0.99999
NICO	8.82E-08	8.08E-15	0.99999
NOT1	8.96E-08	8.06E-15	0.99999
RABT	4.71E-08	2.27E-15	1
YEPE	3.10E-06	9.85E-12	0.99999
ZIMM	6.75E-08	5.05E-15	0.99999
KATA	8.31E-07	7.45E-13	0.99999
MSLT	1.10E-07	1.20E-14	0.99999
PHLW	1.39E-07	3.68E-13	0.99999

**Table 5.** MAE, RMSE, and  $R^2$  of north GNSS velocities predictions from DNN for all stations.

Station	MAE	RMSE	$\mathbb{R}^2$
ADIS	3.46E-06	1.60E-11	0.99999
DRAG	1.17E-05	1.36E-10	0.99998
IISC	7.20E-07	7.57E-13	0.99999
MATE	1.45E-07	2.10E-14	0.99999
NICO	8.82E-08	8.08E-15	0.99999
NOT1	8.96E-08	8.06E-15	0.99999
RABT	4.71E-08	2.27E-15	1
YEPE	3.10E-06	9.85E-12	0.99999
ZIMM	6.75E-08	5.05E-15	0.99999
KATA	8.31E-07	7.45E-13	0.99999
MSLT	1.10E-07	1.20E-14	0.99999
PHLW	1.39E-07	3.68E-13	0.99999

**Table 6**. MAE, RMSE, and R<sup>2</sup> of east GNSS velocities

 predictions from RF for all stations.

Station	MAE	RMSE	R <sup>2</sup>
ADIS	2.02E-05	2.97E-05	0.99991
DRAG	0.000123	0.000742	0.94447
IISC	4.14E-05	7.61E-05	0.99989
KATA	1.45E-05	3.05E-05	0.99970
MATE	6.21E-06	9.15E-06	0.99992
MSLT	1.06E-05	1.46E-05	0.99991
NICO	2.22E-05	9.43E-05	0.99807
NOT1	3.87E-05	0.000207	0.98542
PHLW	2.22E-05	0.000233	0.98902
RABT	5.96E-05	0.000157	0.99633
YEPE	1.16E-05	1.94E-05	0.99987
ZIMM	1.29E-05	5.45E-05	0.99886

**Table 7**. MAE, RMSE, and R<sup>2</sup> of north GNSS velocities predictions from RF for all stations.

Station	MAE	RMSE	R <sup>2</sup>
ADIS	6.29E-05	3.80E-05	0.999777
DRAG	6.47E-05	2.78E-05	0.999194
IISC	0.000118	5.81E-05	0.999292
KATA	2.51E-05	1.28E-05	0.999578
MATE	1.88E-05	6.15E-06	0.999603
MSLT	4.81E-05	2.04E-05	0.998587
NICO	0.000138	4.27E-05	0.991894
NOT1	2.52E-05	8.39E-06	0.999379
PHLW	4.63E-05	1.40E-05	0.998441
RABT	6.99E-05	2.22E-05	0.99749
YEPE	0.000164	2.81E-05	0.972296
ZIMM	0.000148	2.72E-05	0.992477

Fig. 9 illustrates the GPS velocities and their standard deviations, represented as green arrows accompanied by 95% confidence ellipses. In comparison, the velocity predictions and standard deviations derived from the DNN model are depicted with yellow arrows and 95% confidence ellipses to elucidate the data.

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Fig. 3. Trend of east component velocities. (a) The actual data, (b) the DNN predictions, and (c) the RF predictions.



Fig. 4. Trend of east component velocities. (a) The actual data, (b) the DNN predictions, and (c) the RF predictions.



Fig. 5. Trend of north component velocities. (a) The actual data, (b) the DNN predictions, and (c) the RF predictions.



Fig. 6. Trend of north component velocities. (a) The actual data, (b) the DNN predictions, and (c) the RF predictions.







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Fig. 8. Results of the Monte Carlo simulation in the north velocities.



**Fig. 9**. (a) The GNSS geodetic velocity and standard deviations (green arrows with 95% confidence ellipses). (b) Velocity predictions and standard deviations obtained from the DNN algorithm with yellow arrows and 95% confidence ellipses.

#### 4. Conclusion

This study examined the use of DNN techniques to assess horizontal GNSS velocities in a location of active plate tectonics. Thus, 70% of the dataset was used to train the DNN models, with the remaining 30% reserved for model testing and performance evaluation. The findings show that there is no velocity discrepancy between the reference and estimate values of more than 0.0004 mm/yr.. This article contributes a valuable vision of the application of DNN algorithms for geodetic velocity predictions. The findings offer valuable insights for geodynamical research and displacement analysis. Therefore, future research should focus on integrating more advanced methods and improving DNN algorithms to further enhance the accuracy of velocity forecasts.

## **CRediT** Authorship Contribution Statement:

Conceptualization, Alshimaa Y. Abo Gharbia; data collection and analysis, Alshimaa Y. Abo Gharbia, Mohamed Saleh and Ahmed Gomaa; reviewing, Moatamad R. Hassan, Ashraf Elkutb Mousa and Ibrahim Atiatallah Abbas; supervision, Moatamad R. Hassan, Ashraf Elkutb Mousa and Ibrahim Atiatallah Abbas. All authors have read and agreed to the published version of the manuscript.

### **Data Availability Statement**

The data used to support the findings of this study are available from the corresponding author upon request.

#### **Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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#### References

- C. DeMets, R.G. Gordon, D.F. Argus, S. Stein, *Geophysical Journal International*, 101 (1990) 425–478.
- [2] C. DeMets, R.G. Gordon, D.F. Argus, S. Stein, *Geophysical Research Letters*, 21 (1994) 2191–2194.
- [3] M. Yilmaz, M. Gullu, Journal of Earth System Science, 123 (2014) 791–808.
- [4] B. Konakoglu, Acta Geodaetica et Geophysica, 56 (2021) 271-291.
- [5] O.M. Sorkhabi, S.M.S. Alizadeh, F.T. Shahdost, H.M. Heravi, Journal of Asian Earth Sciences X, 7 (2022) 100095.
- [6] O.M. Sorkhabi, M. Milani, S.M. Seyed Alizadeh, *Earth and Space Science*, 9 (2022) e2021EA002202.
- [7] W. Gao, Z. Li, Q. Chen, Journal of Geodesy, 96 (2022) 71.
- [8] W. Jiang, J. Wang, Z. Li, GPS Solutions, 28 (2024) 3.
- [9] Z. Altamimi, P. Rebischung, L. Metivier, X. Collilieux, Journal of Geophysical Research: Solid Earth, 121 (2016) 6109–6131.
- [10] R. Dach, P. Walser, Bernese GNSS Software Version 5.2, Wiley & Sons, 2015.