Figure 24 May Sector Anagement for All

ARTIFICIAL INTELLIGENCE APPROACH FOR PREDICTING *LOCAL CRUSTAL MOVEMENT USING CONTINUOUS OPERATING REFERENCE SYSTEM (CORS) STATIONS

BY Surv. Ing. Christian Kartey Quarcoo

May,2024











Mode Of Presentation

- Background of Study
- Literature Review
- Research Problem
- Research Questions
- Research Objectives
- Materials & Methods
- Results and Discussion
- Conclusion and Recommendations
- Contribution to Knowledge and Science
- ➢ References







Background

It is established that society faces a continuum of everyday risks to major disasters. Hence, it is a great concern that severe natural disasters (e.g., earthquakes, floods, and tsunamis) are generally infrequent but significantly impact society.

➢ For example, destructive earthquakes and other seismic risks greatly impacted various countries resulting in the loss of lives, economic losses and downtimes. Therefore Equal attention must be paid to tackling these problems across the risk spectrum (Songsore, 2006).







- Disasters worldwide require advanced techniques to mitigate risk, as they result in losses of lives and properties, increasing economic expenditure. This requires rigorous experimentation with advanced techniques.
- ➢AI has reduced the risk of earthquake-threatened cities in developed economies by providing precise predictions of seismic activities.
- ➢Rapid advancements in AI have far-reaching implications for engineering practitioners and society, impacting the production and qualities of applications and services, with significant implications for productivity and competition. This is especially true in developing countries, such as Ghana.







- ➢ AI has been applied in many engineering fields as well as geodesy for the determination and prediction of geo-seismic activities of the earth (Reiter *et al.*, 2010).
- > Applications of AI in geodesy has been widely adopted. Notable areas of application include:
- Coordinate transformation (Ziggah *et al.*, 2012; Ziggah *et al.*, 2019; Ziggah *et al.*, 2020, Gullu, 2010; Konakoğlu and Gökalp, 2016; ; Cakir and Konakoglu, 2019)
- Geoid determination (Kavzoglu and Saka, 2005; Veronez, 2011; Erol and Erol, 2013; Cakir and Yilmaz, 2014)

Earth orientation parameter determination (Schuh, 2002; Wang, 2008; Liao, 2012)







Modelling ionospheric Total Electron Content (TEC) (Cander, 1998; Maruyama, 2008; Akhoondzadeh, 2014; Inyurt and Sekertekin, 2019)

Gravity anomaly prediction (Tierra and De Freitas, 2005; Pereira, 2012)

➢ Noise reduction in GNSS signals (Mosavi, 2006; Kaloop and Hu, 2015) and

Crustal movement (Laksari et al.,2012; Yilmaz and Gulu, 2014; Yilmaz, 2013; Argus, 2012; Razin and Mohammedzadeh, 2015; Tierra, 2016). It is important to note that this study is focused on crustal movement.







- ➢ In the last decade, the geoscience community has begun to make robust efforts to apply datadriven techniques to the challenges of crustal movement evaluation, including the application of AI.
- It is established that tidal forces from external bodies cause crustal movement within the earth. Hence, there is an increasing demand for precision and accuracy in crustal movement prediction for geodetic and survey measurements.
- Therefore, highly potent mathematical methods such as AI are needed to model and predict crustal movement. In effect, the impact of crustal movement on the earth's surface could be ascertained and proper mitigation measures applied (Agnew, 2007).
- > To understand the crustal movement geodetically, is by using *Geodetic Point Velocity*.







- Therefore, estimating accurate geodetic point velocity is significant to geoscientific-based communities.
- Several researchers have investigated the velocity field determination in crustal movement (e.g., Demir and Acikgoz, 2000; Nocquet and Calais 2003; Hefty, 2008; Novotny and Kostelecky, 2008).
- In addition, the velocity information can be used to study plate boundary dynamics, seismic site characterization and deformation kinematics (e.g., McClusky, 2000; Hackl et al., 2009; Kanli, 2009; Perez-Pena, 2010; and Pinna, 2011).
- This study adopts an AI approach to develop a computational tool for predicting crustal movement using data from the Licensed Surveyors Association of Ghana (LISAG) Continuous Operating Reference System (CORS).







Research Problem

- ➢ Field fault surveys, satellite imageriess and seismic moment tensor inversions were the primary data sources for understanding tectonic deformation.(Avouac and Tapponnier, 1993; Ding, 1986).
- GPS/GNSS campaigns are used to detect geophysical phenomena such as tectonic movement, fault zones, earthquakes, landslides, volcanoes, and other deformation activities.
- Repeated observations from the GPS/GNSS provide velocity information with high precision and high spatiotemporal resolution (Wonnacott et al., 2011).

Hence, resulting in the varying positioning of geodetic points over time evolution (Duman and Dogan, 2018).







- > Notable empirical methods applied include:
 - I. Kriging
 - II. vector displacement
 - III. least squares collocation
 - IV. linear propagation of errors
 - V. Quasi-Newton model
 - VI. NUVEL model
 - VII. triangulation method
 - VIII. dislocation model
 - X. Ferrell's Green functions
 - XI. VEMOS (SIRGAS velocity model)







- ➢ GPS/GNSS derived velocity field has proven to be an effective source of information for determining the displacement of points in horizontal and vertical space.
- > Its applications also span through but are not limited to the:
 - I. Determination of plate boundaries and their movements
 - II. Displacement of geodetic points
 - III. Crustal motion
 - IV. Geo-kinematic modelling
 - V. The magnitude of earthquakes
 - VI. Velocity of mass center and the surface of the earth,
 - VII. Rotational rate and
 - VIII.Spatial density variations of the earth
 - (Haukson, 2001; Hofman et al., 2006; Heildelberg, 2013 and Younis, 2019).







- Currently, AI techniques and Global Navigation Satellite System (GNSS) Continuously Operating Reference Stations (CORS) data have been coupled for determining and monitoring crustal motion and are perhaps one of the most evident.
- For example, Yilmaz and Gullu (2011) evaluated the geodetic point velocities of 5 stations in Turkey using Backpropagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN) and Kriging.
- It turned out that the BPNN point velocity estimation was better than the RBFNN and Kriging estimations in all geodetic networks.
- Similarly, Tierra (2016) proposed a strategy to interpolate the geodetic point velocities using RBFNN and the empirical VEMOS09 model.
- The results demonstrated that RBFNN could interpolate better than the traditional VEMOS09 model. These mentioned studies have shown the capabilities of AI methods.







- Although AI methods are generally more robust than traditional statistical regression methods, each method has limitations based on how much noise the model can tolerate in data.
- A specific AI method may be effective only for a particular task, and once the object of focus changes, prediction performance may intensely reduce (Li et al., 2019; Du et al., 2019).
- ➢ Research has established that the earth's plate moves at an average 25mm/year rate.
- > However, no research has shown the share of local rates in the global average.
- Therefore, this research applied four(4) AI methods: BPNN, RBFNN, GRNN and GMDH to predict local crustal movement within the southern part of Ghana.
- The key is to select the optimal AI model with higher generalizability that can correctly manage the nonlinearity and high parallelism traits displayed by the varying velocity fields of the earth.







Research Questions & Objetive

Research Questions

The study was to answer the following questions:

- i. What prevailing conditions are needed to achieve maximum local crustal movement prediction performance from the artificial intelligence models?
- ii. What are the accuracies of the artificial intelligence models comparatively?

Research Objective

The main objective of this research is to:

i. Develop an AI prediction model for local crustal movement







Materials and Methods

Materials

- 1. CORS data in Rinex 3.0 format for at least 3 years
- 2. LINUX UBNUTU package
- 3.(Gamit/GlobK)

4. Surfer

5. ArcMap 10.5 6. MATLAB







The methods used include:

- ➢ Back Propagation Neural Network
- ➢ Radial Basis Function Neural Network
- Generalised Regression Neural Network
- ➢Group Method of Data Handling; and

Statistical model evaluators (RMSE, MAE, MSE and R2)







Data Description

The Global Navigation Satellite System (GNSS) campaign data was obtained from the Eight Continues Operation Reference Stations (CORS) established and controlled by the Licensed Surveyors Association of Ghana (LISAG). The initial GNSS receivers were the LeicaGRX1200 series with AS10 antennas. The data was obtained in RINEX 3.0 format with a mast/cutoff angle of 13° and 30 seconds recording rate for 24 hour session daily for the past 3 years.





FIG Norking Week 2024 19-24 May Vour World, Our World: Resilient Environment Accra, Ghana

Materials and Methods (Cont'd)

Station code	Station location	Receiver type (Leica)	Antenna type	Latitude(N)	Longitude(W)	Altitude (m)
LSA1	Accra	GR50	AS10	5°38'01.25411"	0°05'15.51696"	75.574
LSA2	Kumasi	GR50/GRX1200	AS10	6°41'16.60234"	1°37'30.81879"	309.879
LSA3	Tarkwa	GR50/GRX1200	AS10/AR10	5°17'51.70900"	2°00'00.15620"	108.276
LSA4	Koforidua	GRX1200	AS10	6°06'33.35918"	0°18' 8.36489"	222.386
LSA5	Winneba	GRX1200	AS10	4°55'31.74131"	1°46'26.64339"	43.620
LSA6	Tarkoradi	GRX1200	AS10	5°21'38.16636"	0°37'59.50428"	44.902
LSA7	Oda	GRX1200	AS10	5°55'34.32559"	0°59'11.02176"	164.545
LSA8	Но	GRX1200	AS10	6°36'33.32235"	0°27'37.32820"	230.497

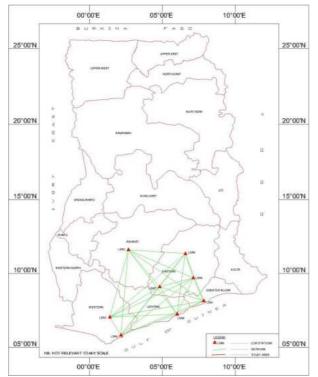
NB:Stations from which GNSS data was used





FIG FIG Working Week 2024 19-24 May World, Our World, O

Materials and Methods (Cont'd)



Map of the study area showing the network of the CORS







- Trimble Business Centre (TBC) was used to process GNSS observation data.
- The RINEX files were imported and the ff info was entered: station name, station ID, type of observation, antenna manufacturer, antenna type, antenna height, receiver type and survey type. Daily baselines were formed in a network involving all stations for the 3 year period.
- The datum chosen was WGS1984 with geographic Cartesian coordinates Nm, Em and Zm and the tropospheric model was the Saastomoinen model.
- 1070 observations were processed for 8 stations and their respective natural coordinates derived.

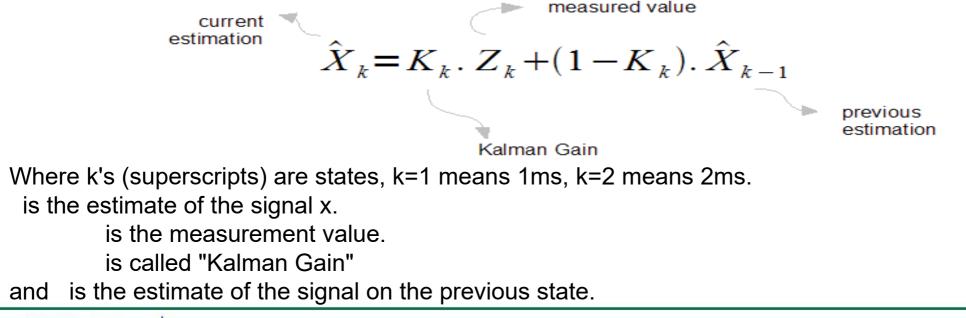






GAMIT/GLOBK is a Linux-based software used to process GNSS data for geophysical analysis, combining solutions from the processing of primary data from space-geodetic or terrestrial observations.

The Kalman filtering models is given as:









AI techniques processes

- Model Prediction Processes were developed to generalize multidimensional input and output mapping challenges.
- 1070 datasets were actualized for eight CORS, divided into two subsets for training and testing.
- Models were able to determine the optimum velocity rate with inputs layers and neurons.





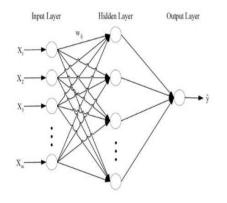
Your World, Our World: FIG Working Week 2024 Resilient Environment and Sustainable and Sustainable **Resource Management** 19-24 May Accra, Ghana for All

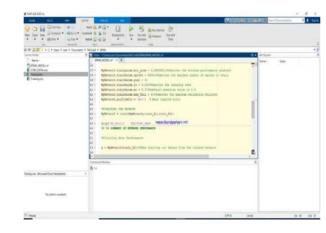
Materials and Methods (Cont'd)

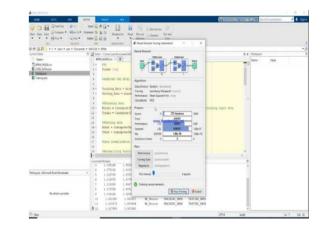
BPNN Architecture and training parameters

It is a feed forward neural network with input, hidden and output layers. It is designed to accommodate multiple hidden layers and inputs are transformed by a mathematical non-linear activation function.

3 inputs, 50 hidden layers with synaptic weights, and one output layer to transform the input-output transformation into a final network output. The selection of a suitable training method, transfer function, number of hidden layers, and number of neurons in the hidden layers is the most important step in creating a BPNN.







BPNN Architecture

Inputting BPNN training parameters

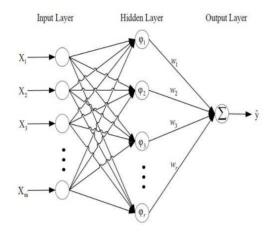
BPNN training process



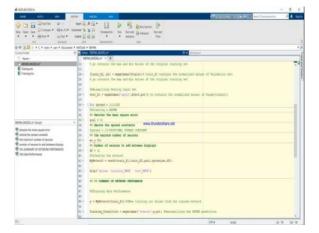


FIG Norking Week 2024 19-24 May Vour World, Our World: Resilient Environment Accra, Ghana

Materials and Methods (Cont'd)



RBFNN Architecture



RBFNN training process

The RBFNN model was trained using a gradient descent learning algorithm with adjustable parameters such as the width parameter and maximum number of neurons in the hidden layer. The optimum architecture was chosen with iterations for the width and maximum number of neurons.



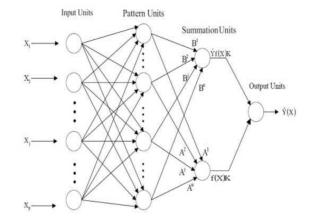


FIG FIG Working Week 2024 19-24 May World, Our World, O

Materials and Methods (Cont'd)

GENERALISED REGRESSION NEURAL NETWORK

GRNN is learning а one pass network composed of input, pattern, summation, and output layers connected by a feedforward connection. Euclidean distances are determined at the pattern layer, and output is delivered to the summing layer.



GRNN Architecture

$$Y(x) = \frac{\sum_{i=1}^{n} w_{i}k(x, x_{i})}{\sum_{i=1}^{n} k(x, x_{i})}$$

where Y(x) is the predicted value of input *x*, *wi* is the activation weight for the pattern layer neurons at *i* and k(x, xi) is the radial basis function kernel between input *x* and training samples, *xi*.

	and Alexandree and Al	_					
	County is in the second party back						
a a a Store Store	base in this . A Annual for						
Balance and Annual Party of the	and the second se						
State of State and States and Street and Str							
Lance Later	Eliza - MADELLAR						
C fare1	(HITE/MED/AF =)						
12" WHICH BEERLIN	10 Vibination Francis Pd						
C Tering die	The Proof of the American Contract of the American Structure of the second state of the second structure of the second structu						
E Taingto	22 / a per contraine the max and man mainers of the uniquital training act						
12 Pa, Martin Pari	28						
	(K. Strain 42, ph) - municipality (1) (1) (1) (1) (1) (1) (1) (1) (1) (1)						
	14. 9 po contación the sua act min values of the creptul training ont						
	28						
	EF MANUNCLEUR POPULATION FOR THE						
	20 - merr 41 - angeinner upply mert pitt to commit to condition while of target inspirit						
	a						
	28.0 The spann = 312100						
NEW WOLLS' SALE	AL Winsting a Pitter						
	11 . 11 dealers the men sparse error week (screate set						
County for most lyant must	32 - grait + fr						
C incide he setted (recent).	12 17 Backs the speed constants						
R Respective-sector diversity	10 motod + 20/11/17/060, Office Obstant						
and the second statement of the second statement of the second se	18 11 The maximum moment of records						
THE REPORT OF MUSICAL HANDLINES	10 + m. + 40						
槽 Tel ally femanary	11 . 11 surger of measure to and between manager						
	18 af - 12						
	as assistently the retained						
	4) * Balevers + medicipal, 41, crait, 37, mel, crassfull, 471						
	44						
	404 displ'arread incomplete per mail's						
	at the summary of spreamer personality						
	at bettalling data hert-menn						
	et all						
	27 y = Reference reason all blocks in the second second second.						
45	2018 with	to state the t					

GRNN training process

The optimal spread constant input was 29 and 40, with the best correlation coefficient and lowest MSE for both training and testing data sets.

PLATINUM SPONSOR

Strimble



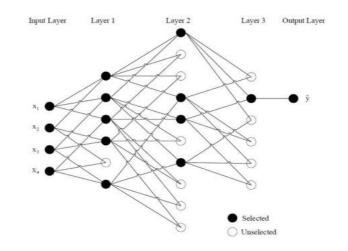
FIG FIG Working Week 2024 19-24 May Vour World, Our World: Resilient Environment Accra, Ghana

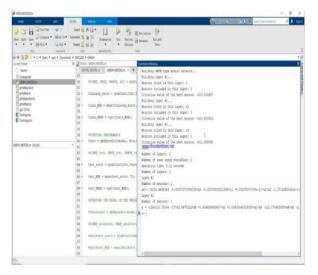
Materials and Methods (Cont'd)

GROUP METHOD OF DATA HANDLING

Ivakhnenko (1970) created the Group Method of Data Handling (GMDH) approach to model non-linear, unstructured, and complicated systems. It uses a multilayer network made up of many quadratic neurons to translate input variables into matching target variables. The Kolmogorov-Gabor polynomial is used to characterize the interactions between inputs and outputs.

Equation (4.12) of the Kolmogorov- Gabor polynomial, a multilayer network of second order, is used by GMDH to characterize the intricate nonlinear interactions between the system's inputs and outputs (Assaleh et al., 2013).





GMDH Architecture

GMDH training process





FIG Norking Week 2024 19-24 May Nour World, Our World,

RESULTS AND DISCUSSION

INTERPRETATIONS OF LOCAL CRUST MOVEMENT PREDICTIONS RESULTS

- Four ANN models where used to in the training and testing for the prediction of the local crust movements in the directions X, Y and Z.
- An optimum number of neurons where selected for the training. The data was divided into 2; (80%) for the training and the second
 (20%) for the testing of the prediction

These were then evaluated using some statistical indicators such as

RMSE, MSE, MAE, and Coefficient of determination (R²).





FIG Norking Week 2024 19-24 May Accra, Ghana Your World, Our World: Resilient Environment Accra, Ghana

Materials and Methods (Cont'd)

Model Prediction Performance

Predictive models for Geodetic Point Velocities analyzed using statistical performance indicators

 $MSE = \frac{1}{n}\sum_{i=1}^{n} (o_i - p_i)^2$

where *n* is the total number of test samples, *oi* are the observed values, *p* are the predicted values is the mean of the observed values and is the mean of the predicted values .

RMSE =
$$\sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (o_i - p_i)^2}$$

An evaluation of the various prediction models was done by plotting the observed against the predicted with a 1:1 line, a 95% confidence interval (CI) (Equation (4.86)) and 95% prediction interval (PI)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| o_i - p_i \right|$$

$$R^{2} = \frac{\left(\sum_{i=1}^{n} (o_{i} - \overline{o})(p_{i} - \overline{p})\right)^{2}}{\sum_{i=1}^{n} (o_{i} - \overline{o})^{2} \times \sum_{i=1}^{n} (p_{i} - \overline{p})^{2}}$$

where is the mean of the predicted values, σ is the population standard deviation, $Z_{a/2}$ is the Z value for the desired confidence level a and *n* is the number of predicted values. At a 95% Confidence Interval, $Z_{a/2} = 1.96$







RESULTS AND DISCUSSION (Cont'd)

20% of the dataset was used to assess the performance of the model. The geocentric Cartesian coordinates for the 208 points were known, and the predicted values of the crustal velocities from the models were compared with the observed values.

$$E_{(Model)} = V_{(observed)} - V_{(predicted)}$$

where $E_{(Model)}$ is the difference of the model being considered, $V_{(observed)}$ for observations and

 $v_{(predicted)}$ is the predicted model values





FIG FIG Working Week 2024 19-24 May Vour World, Our Wor

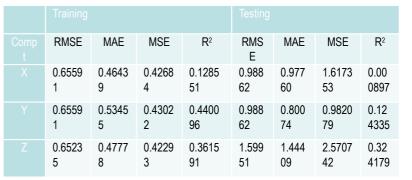
RESULTS AND DISCUSSION (Cont'd)

	Training					Testing				
	RMSE	MAE	MSE	R²	RMSE	MAE	MSE	R²		
Х	0.6752	0.4914	0.4559	0.0691	1.7616	0.4643	1.3272	0.004		
	33	79	39	54	23	97	61	135		
Y	0.6694	0.5540	0.4481	0.4167	1.0241	0.8676	1.0489	0.214		
	45	65	57	52	59	61	02	994		
Z	0.6694	0.0121	0.4822	0.4274	1.0241	1.0758	1.2539	0.298		
	45	58	09	87	59	31	64	106		

The BPNN Model Performance Criteria Results

Compt.	RMSE	MAE	MSE	R ²	RMSE	MAE	MSE	R^2
Х	0.655	0.464	0.000	0.128	0.988	0.9776	0.855	0.000
	912	397	334	551	625	09	997	897
Y	0.655	0.534	0.534	0.440	0.892	0.8007	0.796	0.124
	912	559	559	096	702	49	918	335
Z	0.652	0.477	0.534	0.361	0.791	1.4440	0.626	0.324
	352	789	559	591	420	930	345	179

GRNN Model Performance Criteria Results



RBFNN Model Performance Criteria Results

	Training								
Com pt	RMSE	MAE	MSE	R ²	RMSE	MAE	MSE	R ²	
	0.6998 51	0.5076 95	0.4897 91	0.0458 68	1.2232 58	0	1.3272 61	0.2020 89	
Y	0.7419 93	0.5972 00	0.5505 55	0.3183 63	0.8424 00	0.6940 23	0.7096 37	4.10E- 05	
Z	0.9177 24	0.6684 61	0.8422 18	0.0640 61	0.9519 27	0.8944 08	0.9061 65	4.35E- 01	

GMDH Model Performance Criteria Results

PLATINUM SPONSOR

Strimble.



FIG Norking Week 2024 19-24 May Accra, Ghana Your World, Our World: Resilient Environment Accra, Ghana

RESULTS AND DISCUSSION (Cont'd)

□ This study assessed the capability AI techniques of BPNN, GMDH, RBFNN and GRNN as alternate predictive tools for Geodetic Point Velocity. It was found that no AI model produced the least MSE, RMSE, R2 and MAE for all 3 components, but some models were good in training and predicting some components of velocities with high accuracies. This suggests that the closer the values of MSE, RMSE R2 and MAE are to zero, the better the prediction capability of the model.





FIG Norking Week 2024 19-24 May Nour World, Our World,

RESULTS AND DISCUSSION (Cont'd)

The GMDH ANN model outperformed the other candidate models in terms of geodetic point velocity prediction results. The BPNN model was able to learn and generalise well during the training, but could not produce acceptable results across the entire testing dataset. The RBFNN results for Vz had the highest R2 value of 0.324179. The results of this study showed that the GMDH model had a better capability of producing reliable results than the other AI models, as it had the least statistical values. Other AI models (RBFNN, GRNNS and BPNN) also produced comparable and satisfactory prediction results in some components of the geodetic point velocities. This suggests that other AI models can also be used to predict geodetic point







CONCLUSIONS AND RECOMMENDATIONS

CONCLUSION

This study investigated the prediction of Geodetic Point Velocities in Ghana using four AI techniques. Four statistical evaluation methods were used to assess the suitability of the proposed models. The GMDH model was selected based on statistical performance criteria.

RECOMMENDATION

From results, it is recommended that:

i. These AI techniques in predicting GPV should be adopted by Geoscientists in forecasting seismic activities of the earth and its related fields where applicable.





FIG Norking Week 2024 19-24 May Vour World, Our World: Resilient Environment Accra, Ghana

CONCLUSIONS AND RECOMMENDATIONS (Cont'd)

- i. AI algorithms be investigated and formulated to carter for the noises in the data obtained from the GAMIT/GLOBK processing.
- ii. A research be taken to cover the whole of the country to determine the extent of crust movement nationwide by increasing the number of CORS.
- iii. The number of neurons and epochs should be increased iteratively to ascertain their effects when predicting.







CONCLUSIONS AND RECOMMENDATIONS (Cont'd)

Different datasets be utilized to evaluate the influence of point density on the geodetic point velocity prediction outcomes.

In this project, the candidate models provided reasonable predictions, so it can be an alternative tool for predicting the GPVs.

The prediction of accurate GPV needs to be further researched and discussed. The candidate models under studies had their strength in predicting some variables right to the highest accuracies.

For instance the prediction result of BPNN model was high with the Vx component, the GRNN was good in predicting accurately the Vy & the GMPH was good in both Vx & Vy with a little ambiguity with the Vz variable.

Therefore, a hybrid model of these for when researched will not be farfetched to determined its

contribution to the accuracy factor.







Proposed Contribution to Knowledge/Science

The following contributions have been made to knowledge/science:

- Application of AI in solving geodetic challenges in Ghana and to some extend Sub-Sahara Africa due to the homogeneity of the West African plate.
- Profess the best ANN model that is best-fit for Ghana
- To add on to existing knowledge and data in the field of geodesy.

The beneficiaries:

- Geodesists, geographers, Researchers, Geomatic engineers, etc.
- Various academic institutions with related research interest
- The Lands Commission
- Serve as a reference guide or material for knowledge building in similar area.





FIG Working Week 2024 Resilient Environment and Sustainable 19-24 May Accra, Ghana Resou

Your World, Our World: **Resource Management**

SUSTAINABLE G ALS International Federation of Surveyors supports the Sustainable Development Goals

Commission 5

GNSS CORS Reference Stations and Networks SDGs GOALS 11 & 15 - 13 Serving Society for the Benefit of People and Planet











FIG Norking Week 2024 19-24 May Vour World, Our World: Resilient Environment Accra, Ghana

OYI WALA DON THANK YOU



