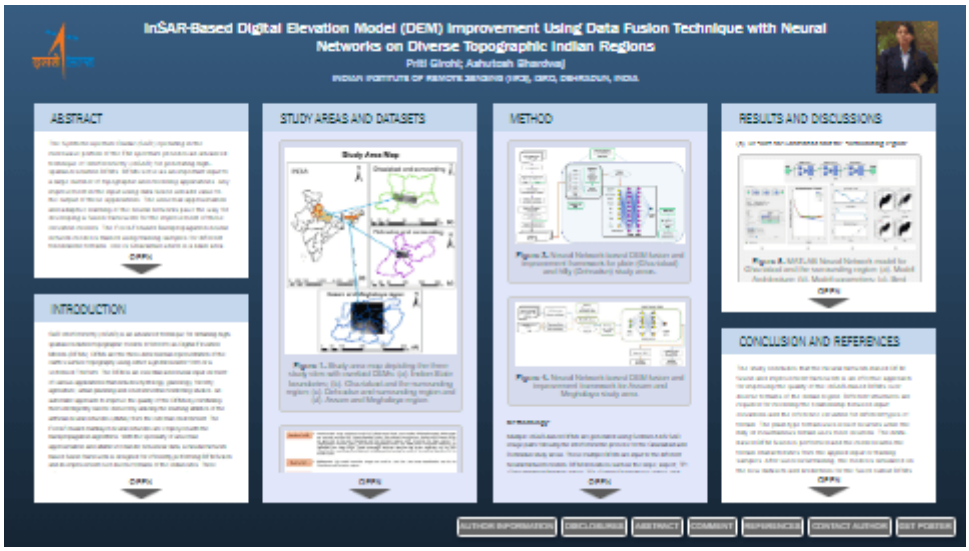
InSAR-Based Digital Elevation Model (DEM) Improvement Using Data Fusion Technique with Neural Networks on Diverse Topographic Indian Regions



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PRESENTED AT:

ABSTRACT

The Synthetic Aperture Radar (SAR) operating in the microwave portion of the EM spectrum provides an advanced technique of Interferometry (InSAR) for generating high-spatial-resolution DEMs. DEMs serve as an important input to a large number of topographic and modeling applications. Any improvement in the input using data fusion will add value to the output of these applications. The universal approximation and adaptive learning of the neural networks pave the way for developing a fusion framework for the improvement of these elevation models. The Feed-Forward Backpropagation neural network model is trained using training samples for different topographic terrains, one is Ghaziabad which is a plain area and the other is the Dehradun region which is a hilly terrain area. The elevation values from multiple input InSAR-based DEMs generated using Sentinel-1A/B images and values of DEM derivatives such as slope, aspect, topographic position index (TPI), terrain ruggedness index (TRI), vector roughness measure (VRM) are used along with Land Use Land Cover (LULC) classes information from Sentinel-2A multispectral data, for the preparation of training samples. The reference elevation used for training is obtained from the ICESat-2 ATL08 Land and Vegetation height product. By removing outliers and using hyperparameter optimization for selecting the best fit neural network architecture, the models are trained. The plain terrain model uses a Log-sigmoid with a simpler structure while the hilly terrain uses a linear activation function with more neurons in hidden layers. The trained models produce fused DEMs on the test areas and an accuracy analysis is performed. The root mean square error (RMSE) is estimated for evaluating the obtained fused DEMs with the TanDEM-X 90m DEM. A more complex mountainous terrain is selected from the north-eastern Himalayan portions of the Assam and Meghalaya region, where two ALOS PALSAR Radiometrically Terrain Corrected (RTC) 12m high-resolution DEMs are fused and improved using the neural network fusion framework. The fused output DEMs shows improvement with lower RMSE values as compared to the individual input DEMs. The plain terrain has 4.34m; hilly terrain shows 10.95m and mountainous terrain has 7m RMSE which is very low in comparison to the individual DEMs RMSE.

INTRODUCTION

SAR Interferometry (InSAR) is an advanced technique for obtaining high-spatial-resolution topographic models referred to as Digital Elevation Models (DEMs). DEMs are the three-dimensional representation of the earth's surface topography using either a gridded-raster form or a vectorised TIN form. The DEM is an essential and crucial input element of various applications that includes hydrology, glaciology, forestry, agriculture, urban planning and environmental monitoring studies. An automatic approach to improve the quality of the DEMs by combining them intelligently can be derived by utilizing the learning abilities of the artificial neural networks (ANNs) from the external environment. The Feed-Forward multilayer neural networks are employed with the backpropagation algorithms. With the speciality of universal approximation and abilities to handle non-linear data, a Neural Network based fusion framework is designed for efficiently performing DEM fusion and its improvement over diverse terrains of the Indian sites. Three different terrains plain, hilly and complex, are selected for this study. Different ANN structures are implemented using programming and MATLAB Neural Network (NN) toolbox. The input feature vector constitutes the elevation values from multiple InSAR DEMs generated from Sentinel-1A/B image pairs for plain and hilly study sites along with the DEM derivatives and LULC information for that area. The DEM derivatives used while training the models help in modelling the relationship between the input elevation and the reference elevations. While ALOS PALSAR RTC 12.5m DEM products are used for the third complex terrain site. The precise ICESat-2 ATL08 Land and Vegetation height product provides for the reference elevations or the known output for the training of the NN models. Applying heuristics and performing hyperparameter optimization for selecting the best architecture, the NN models are trained by applying a sufficient number of training samples for each area. The Neural Networks once trained successfully using the training and validation data, are tested on the new data samples from the test areas and the fused elevation output from the models is obtained. The NN models provide the predictions for elevation values of the fused DEMs by learning the terrain properties from the provided training samples. This work is relevant in the context of various topographical and quantitative modelling applications where the DEMs serve as a primary input. Improved input applied to an application will produce better-quality output.

STUDY AREAS AND DATASETS

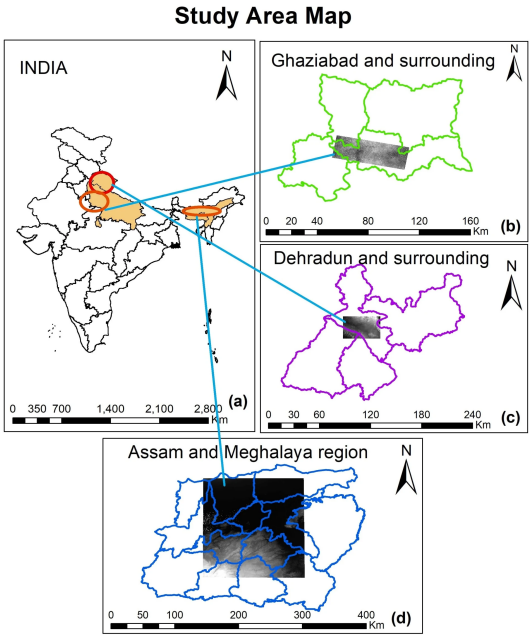


Figure 1: Study area map depicting the three study sites with overlaid DEMs: (a). Indian State boundaries; (b). Ghaziabad and the surrounding region; (c). Dehradun and surrounding region and (d). Assam and Meghalaya region.

Sentinel-1 A/B:	Interferometric image pairs from Level-1 SLC (Slant-range Single Look complex) IW (Interferometric Wide swath) are selected using the ASF (Alaska Satellite Facility) data search & baseline tool. Multiple InSAR based DEMs are generated for the plain Ghaziabad and hilly Dehradun regions. DEM derivatives like slope, aspect, TPI (Topographical Position Index), TRI (Terrain Ruggedness Index) and VRM (Vector Roughness Measure) are generated from these DEMs. These topographic attributes describes the terrain properties and the DEM characteristics quantitively, thus helping in modelling and enhancing the quality of the predicted elevations for the fused outputs.
Sentinel-2A :	Multispectral 10m spatial resolution images are used for Land Use Land cover classification map for the Ghaziabad and Dehradun regions.
ALOS PALSAR:	ALOS PALSAR radiometrically terrain corrected (RTC) 12.5m high-resolution DEM product are used for the Assam and Meghalaya region having complex terrain. Several tiles of this product are accessed from the ASF data search tool and mosaicked to obtain an input DEM for the area.
ICESat-2 ATL08 data:	ICESat-2 (Ice, Cloud, and Land elevation satellite) spaceborne altimetry photon-based ATL08 (Land and Vegetation) height product is used as a reference elevation data for training the neural networks and accuracy assessment of the output fused DEMs.
TanDEM-X 90m DEM:	TanDEM-X 90m DEM is used for accuracy assessment of the fused DEMs over Assam and Meghalaya region.

Figure 2: Datasets used and their purpose

Study areas:

(a). Ghaziabad and its surroundings: The first study area is from Ghaziabad and its surrounding regions from the state of Uttar Pradesh. This is a relatively plain terrain region. The InSAR DEM overlaid on the study area (figure1.b) shows the geographical extent covering from 77° to 78° E Latitude and 28° to 29° N Longitude, that is an area of 777.9 sq. Km. The average elevation of this area is around 214m and the values range from 60m in the eastern part to 300m in the northwest parts. The climate is tropical monsoon type and the terrain relief is featureless with fertile land. This region includes highly dense-urban and rural built-up settlements. Other LULC classes include agricultural fields, croplands, barren lands, roads-highways, and a river body.

(b). Dehradun and its surroundings: The hilly terrain region is selected from Dehradun and its surrounding regions. It is the largest, most populated, and the capital of the state of Uttarakhand. Its location is in the foothills of the Himalayas and the Shivalik range in the Doon valley. The latitude and longitude extend from 77°34′ to 78°18′ E and 29°58′ to 31°2′

N covering an area of 3088 sq. Km. Two major rivers the Ganges and the Yamuna flow across this region. Geographically this region consists of highlands and hills with cooler temperatures and dense forest ranges. The elevation values of this hilly terrain of this region range from 410m in the town area to around 2000m in the Mussoorie hills. The land cover includes dense built-ups in the city of Dehradun surrounded by dense forest covered with large tree canopies. This region is highly vulnerable to natural disasters like seasonal floods, landslides, and earthquakes.

(c). Assam and Meghalaya regions: This study area is from the North-Eastern Himalayan region covering several districts of Assam and Meghalaya states. The geographic extent of this region covers from 25.40’ to 26.85’ N Latitude and 91.61’ and 93.07’ E Longitude. The portion of Assam has Northern Himalayas, Brahmaputra floodplains, and plateaus in the southern parts. The temperate and tropical rainforest-type climate receives heavy rainfalls and the height of hills ranges from 300m to 2000m. The Brahmaputra, older than the Himalayas, flows through this state, eroding the place and forming steep gorges and floodplains. While the Meghalaya region has a highland Shillong plateau and several faults. The region contains the oldest rocks from Precambrian to the new alluvium formations. This region observes active tectonics due to the collision of Indian & Tibetan landmasses and is of geological importance. The overall elevation values for the whole region range from 1m to around 2000m.

METHOD

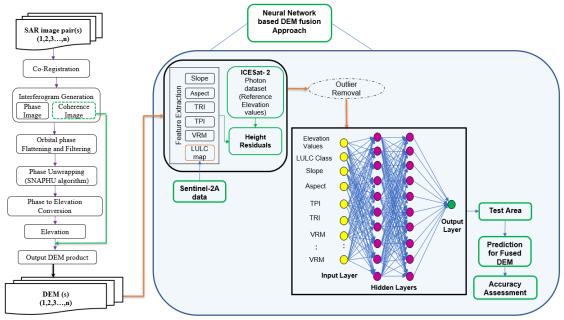


Figure 3: Neural Network-based DEM fusion and improvement framework for plain (Ghaziabad) and hilly (Dehradun) study areas.

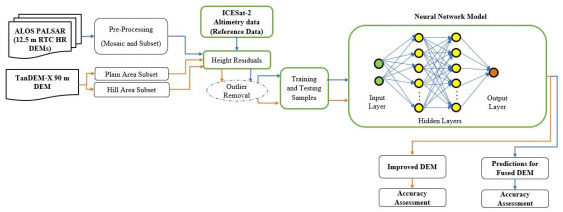


Figure 4: Neural Network-based DEM fusion and improvement framework for Assam and Meghalaya study area.

Methodology:

Multiple InSAR-based DEMs are generated using Sentinel-1A/B SAR image pairs following the interferometric process for the Ghaziabad and Dehradun study areas. These multiple DEMs are input to the different Neural Network models. DEM derivatives such as the slope, aspect, TPI (Topographical Position Index), TRI (Terrain Ruggedness Index), and VRM (Vector Roughness Measure) along with the LULC information constitute the input feature vector for the models. A simple ANN structure is designed to have an input, two hidden, and an output layer. One way to implement the neural networks is with python programming which uses Keras (Tensorflow) library. The NN models are sequential dense layer feed-forward multilayer models with gradient descent backpropagation algorithms and Adam (Adaptive Moment) optimizer. Another way is by using MATLAB Neural Network (NN) Toolbox where a faster training algorithm of Levenberg Marquardt (TRAINLM) is used for training the Feed Forward Backpropagation neural network models. The training data is filtered for outlier removal using values within the range of a second standard deviation. These are applied to the input layer of the NN models along with the reference elevations from the precise ICESat-2 ATL08 (Land and Vegetation) height product. Hyperparameter optimization is performed to select the parameters for a best-fit NN model for each study area. Thus, by selecting the suitable number of neurons, activation function, number of layers, and loss function, different NN architectures are trained using training samples and the best model is saved. The NN for both study sites has an input layer, two hidden layers, and an output layer with 31 – 21 - 15 – 1 node respectively for the plain Ghaziabad region and 31 – 64 – 128 – 1 node respectively for the hilly Dehradun region. Suitable activation functions are selected for each layer- Log-Sigmoid for plain and Linear for hilly study areas. The loss function (MSE) is observed for determining the overfitting or underfitting problems while training. The successful training of the models predicts elevation values for the test area. Similarly, for the third site of Assam and Meghalaya regions which has a complex terrain, elevation values of the ALOS PALSAR RTC 12.5m product is applied to the input layer along with the reference elevations and with Linear activation function, different NN structures are designed, for the complete region and valley and mountainous regions separately. The output elevation values of the fused DEMs from the trained models are then assessed for their accuracy by estimating the statistical parameters such as the RMSE (Root Mean Square Error), LE90 (Linear Error at 90th percentile), Mean Error (ME) and percentage improvement factor (%IF). The elevation values of the fused output DEMs are checked with the toposheets of each study area that they fall within the correct range. Due to the complex hilly terrain of this region, geometric distortions of foreshortening, layover, and shadow are present in the SAR images. The TanDEM-X 90m DEM product is improved over this region using the Neural Network models and the results are assessed by estimating the percentage improvement factor (%IF).

RESULTS AND DISCUSSIONS

(a). Results for Ghaziabad and the surrounding region:

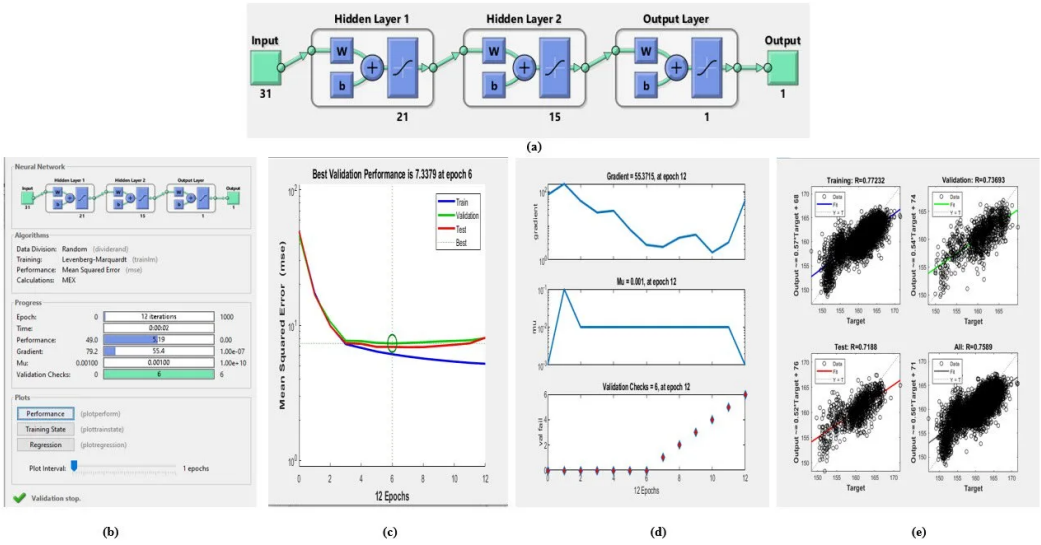


Figure 5: MATLAB Neural Network model for Ghaziabad and the surrounding region: (a). Model Architecture; (b). Model parameters; (c). Best performance while training; (d). Training state of the model; (e). Regression plot between target and output data.

DEMs	RMSE (m)	LE90 (m)	Improvement Factor (%IF) for Keras Model	Improvement Factor (%IF) for MATLAB Model
DEM 1	12.03	19.78	71.24	63.92
DEM 3	28.85	47.45	88.01	84.96
DEM 6	31.93	52.52	89.16	86.41
DEM 7	24.39	40.12	85.81	82.20
DEM 8	64.64	106.33	94.65	93.28
ANN Prediction (Keras Model)	**3.46**	5.69	--	--
ANN Prediction (MATLAB model)	**4.34**	7.14	--	--

Figure 6: Results for Neural Network-based DEM fusion approach for Ghaziabad and the surrounding region.

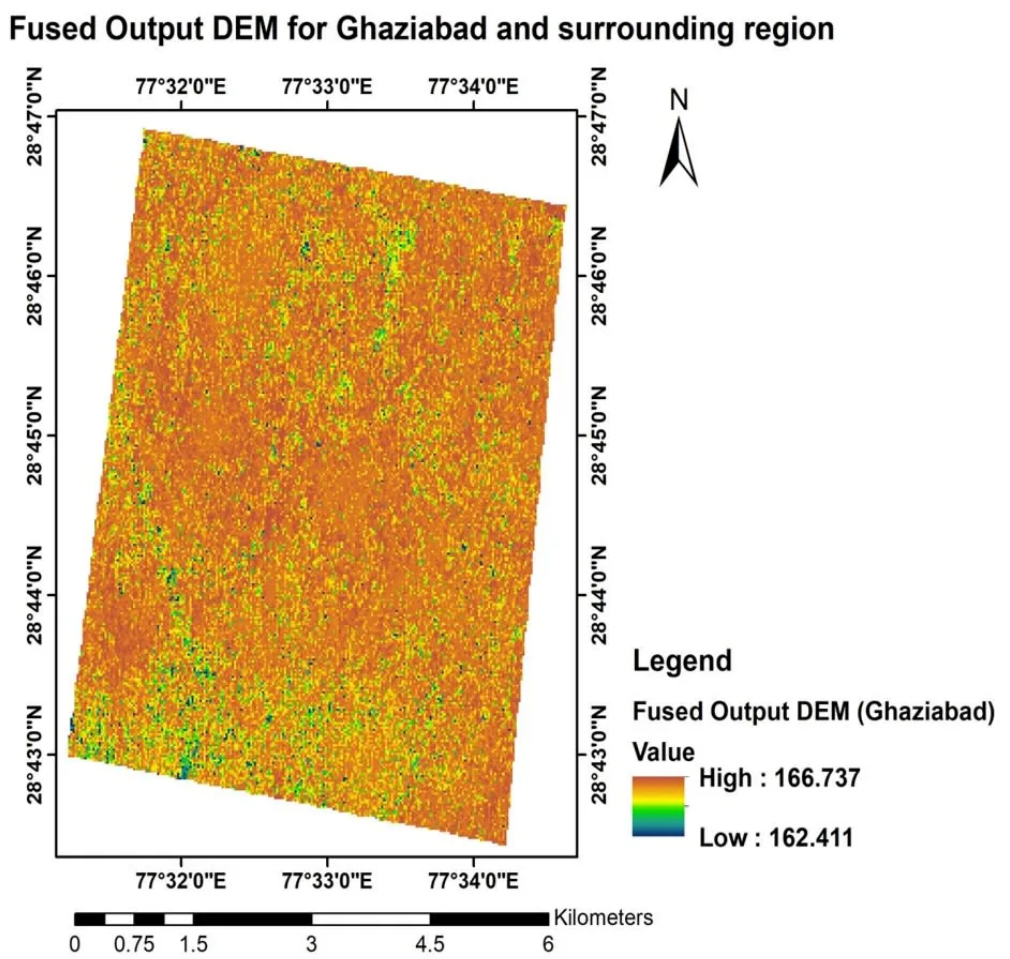


Figure 7: Fused output DEM obtained for test area using Neural Network-based fusion approach for (Plain) Ghaziabad and the surrounding region.

The Keras-based and the MATLAB NN-toolbox neural network model (Figure 5) uses the same structure for this plain terrain area having 31- 21- 15- 1 neuron in the input, first hidden layer, second hidden layer, and the output layer respectively. The "Sigmoid/ Log-sigmoid" activation function models this terrain appropriately. Only the training algorithm used in the MATLAB NN toolbox is TRAINLM. A total of 6694 training samples are used for training and validation of the model. After successful training, the model is simulated on the new dataset from the test area. The trained model predicts the elevation value for the fused output DEMs. The output of DEM fusion from the model is assessed with the TanDEM-X 90m DEM. The fused output DEM from the ANN model in the Ghaziabad and surrounding regions is represented by the map in Figure 7. The statistical analysis of the fused output DEM shows that the RMSE values (Figure 6) are lower around 3.46 and 4.34m for the fused DEMs in comparison to the input individual DEMs. The Linear error (LE90) is very low for the fused DEMs around 5.69 and 7.14 m for the Keras and MATLAB-based models respectively. This reveals a significant improvement of the fused DEMs in terms of accuracy over the input InSAR DEMs for the plain region obtained effectively with the use of Neural Networks.

(b). Results for Dehradun and the surrounding region:

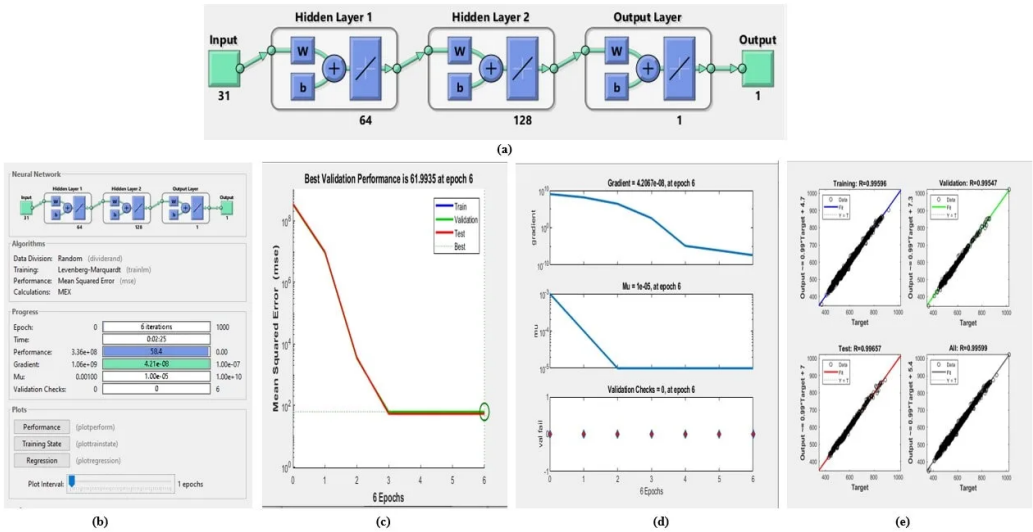


Figure 8: MATLAB Neural Network model for Dehradun and the surrounding region: (a). Model Architecture; (b). Model parameters; (c). Best performance while training; (d). Training state of the model; (e). Regression plot between target and output data.

DEMs	RMSE (m)	LE90 (m)	Improvement Factor (%IF)
DEM 1	51.91	85.38	78.91
DEM 2	20.41	33.57	46.35
DEM 3	63.02	103.66	82.62
DEM 4	26.05	42.85	57.96
DEM 5	17.23	28.34	36.45
ANN Prediction (MATLAB model)	**10.95**	18.01	--

Figure 9: Results for Neural Network-based DEM fusion approach for Dehradun and the surrounding region.

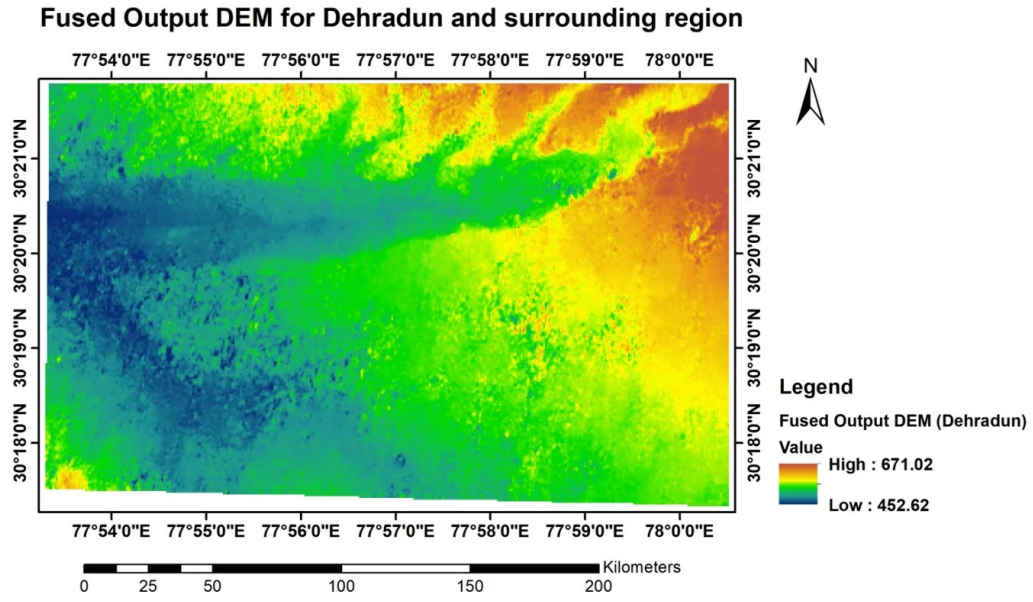


Figure 10: Fused output DEM obtained for test area using Neural Network-based fusion approach for (Hilly) Dehradun and the surrounding region.

The hilly terrain region of Dehradun and its surroundings required more neurons in each hidden layer that is 64 and 128 units for its modeling. The activation function used in this case is “Linear/PURELIN” in each model. A total of 3423 samples are used for this case after outlier removal. However, the Keras-based models were not able to produce satisfactory results on the new datasets. The MATLAB-based model (Figure 8) with a faster training algorithm, produces output fused DEM for the hilly and undulating terrain as represented in the map (Figure 10). The statistical accuracy analysis of the Fused output DEM with the TanDEM-X 90m DEM exhibits a remarkable improvement in terms of reduced RMSE and LE90 values for the fused DEMs over the input DEMs. The RMSE of fused DEMs is reduced to 10.95m as compared to the input DEMs (Figure 9).

(c). Results for Assam and Meghalaya region:

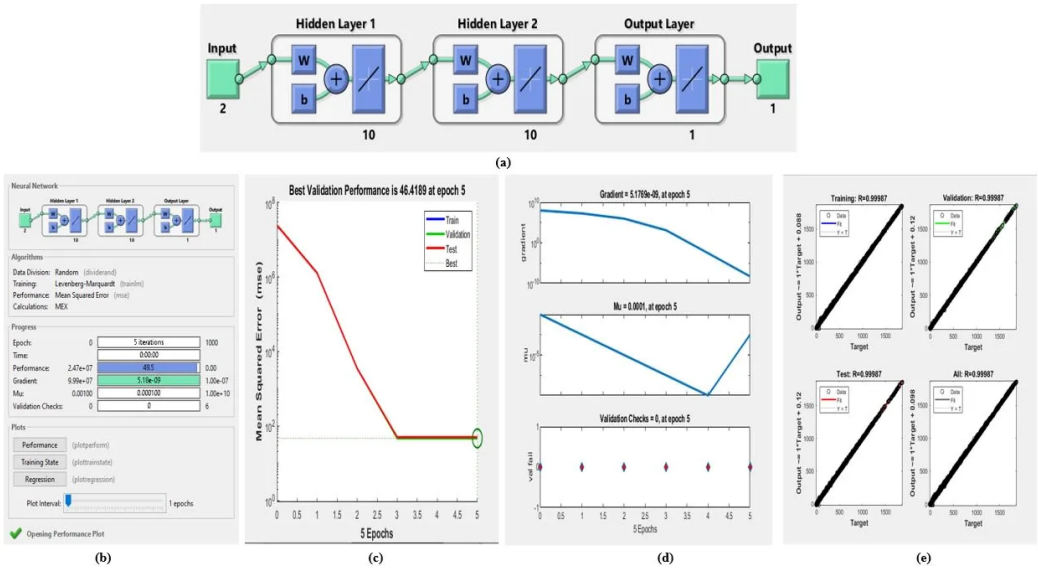


Figure 11: MATLAB Neural Network model for Assam (plain valley) portion: (a). Model Architecture; (b). Model parameters; (c). Best performance while training; (d). Training state of the model; (e). Regression plot between target and output data.

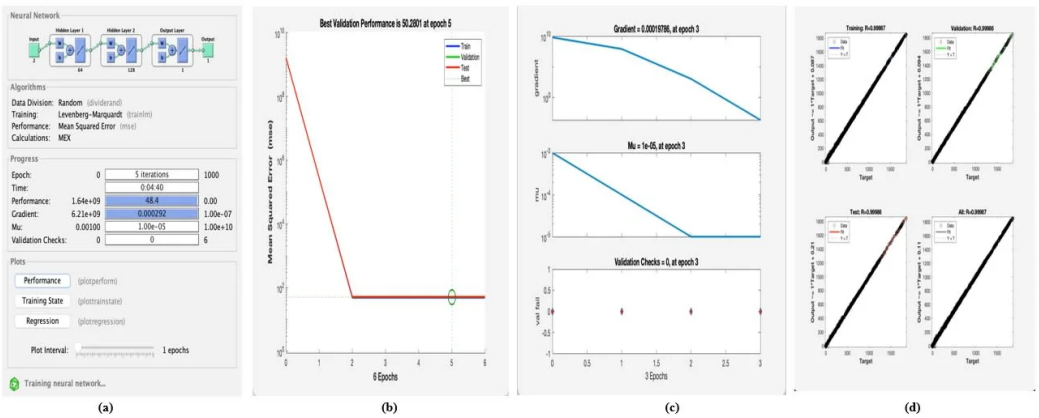


Figure 12: MATLAB Neural Network model for Meghalaya (mountainous plateau) portion: (a). Model Architecture & Model parameters; (b). Best performance while training; (c). Training state of the model; (d). Regression plot between target and output data.

Total ICESat-2 footprints (22767 points)			
	Input DEM 1	Input DEM 2	Fused DEM
ME (m)	7.72	7.74	0.03
RMSE (m)	11.12	11.11	7.00
Plain Area (12175 Points)			
ME (m)	3.21	3.20	-0.03
RMSE (m)	5.14	5.12	3.82
Mountainous Area (10591 Points)			
ME (m)	12.91	12.95	-0.01
RMSE (m)	15.35	15.34	8.18

Figure 13: Results for Fused DEMs for Assam (plain) and Meghalaya (Mountainous) regions using ICESat-2 data.

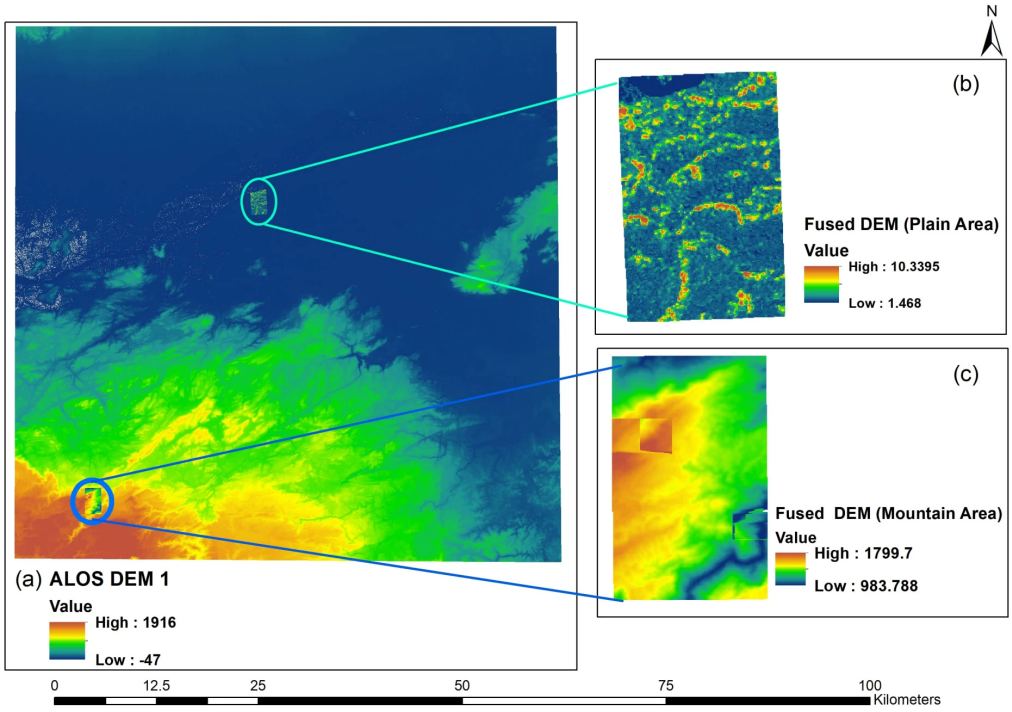
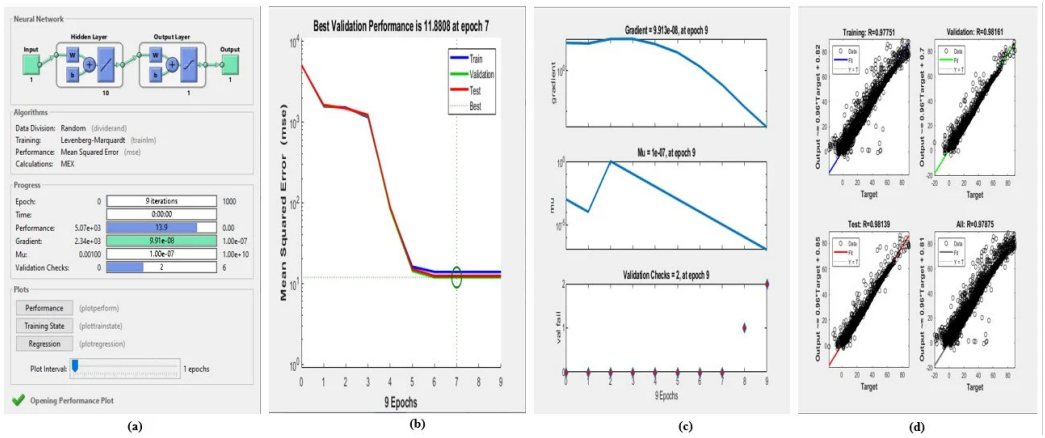


Figure 14: Fused output DEM obtained for test area using Neural Network-based fusion approach (a). Input ALOS DEM depicting study extent with an overlay of fused outputs; (b). Enlarged view of Fused output DEM for Assam (plain valley) portion and (b). Enlarged view of Fused output DEM for Meghalaya (mountainous plateau) portion.

This is a large study area with complex terrain having both a floodplain valley region in the Assam portion and a highland plateau mountainous region in the Meghalaya portion, separate models are designed for the two portions. The training and validation dataset contains total of 22767 sample points. Linear (PURELIN) activation function is used for modeling this terrain. The plain (valley) portion uses a model with structure 2-10-10-1 (Figure 11) while the mountainous portion has a model of 2-64-128-1 (Figure 12) units in the layers. The predictions for fused output DEM from the model are assessed for accuracy by calculating Mean Error (ME) and RMSE taking ICESat-2 as a reference (Figure 13). The RMSE obtained for the plain region is around 3.82m which is lower than the RMSE of 5m for the input DEMs. The fused DEM in the mountainous region has attained an RMSE of 8.18m which is remarkably low in comparison to the 15.35m value of RMSE for input DEMs.

(d). Results for TanDEM-X 90m DEM improvement over geometric distortion areas:



(a) (b) (c) (d)

Figure 15: MATLAB Neural Network model for implementing DEM improvement over geometric distortion affected areas: (a). Model Architecture & Model parameters; (b). Best performance while training; (c). Training state of the model; (d). Regression plot between target and output data.

Total ICESat-2 footprints (22994 points)			
	Input TDM	ANN Prediction	% IF
RMSE (m)	11.21	7.42	33.83
Plain Area Points			
RMSE (m)	4.64	3.64	21.57
Mountainous Area Points:			
RMSE (m)	14.07	8.85	37.13
Near Ground Points (having 0 to 0.5 m height error)			
Plain Area Points:			
RMSE (m)	0.26	0.14	46.76
Mountainous Area Points			
RMSE (m)	0.29	0.13	54.59

Figure 16: Results for the TanDEM-X 90m DEM in Assam and Meghalaya region

A separate model is trained with input as the elevations (22994 samples) from the TanDEM-X 90m DEM, with a simple structure of 1-10-1 neurons and linear activation function. Accuracy assessment of the results shows a significant 33.8% improvement for the geometric distortion-affected areas. Separately for the Plain portions, the improvement factor is about 21.57% while in mountainous portions the percentage improvement is around 37.13%. Further, for near-ground points (having height error between 0 to 0.5m) the TanDEM-X 90m DEM is improved upto 46.76% in the plain portion while 54.59% of improvement is achieved in the mountainous regions.

CONCLUSION AND REFERENCES

The study concludes that the Neural Network-based DEM fusion and improvement framework is an effective approach for improving the quality of the InSAR-based DEMs over diverse terrains of the Indian region. Different structures are required for modeling the relationship between input elevations and the reference elevation for different types of terrain. The plain type terrain uses lesser neurons while the hilly or mountainous terrain uses more neurons. The ANN-based DEM fusion is performed and the model learns the terrain characteristics from the applied input or training samples. After successful training, the model is simulated on the new datasets and predictions for the fused output DEMs are obtained. The developed data-driven neural network models efficiently perform DEM fusion and improvement over plain, hilly, and complex terrains. Significant improvements in terms of statistical parameters are observed in the three study areas. The improved accuracy infers that the implementation of this approach is successful over the three study areas. Although both approaches produce similar results, the MATLAB NN-Toolbox helps in designing ANN models faster with much faster-converging training algorithms, the Keras-based NN models employ more heuristics and customized approaches where suitable architecture can be iteratively tested for specific terrain. Finally, the developed models performed effectively well in obtaining improved and better quality DEMs over the plain, hilly and complex terrains of the Indian region.

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DISCLOSURES

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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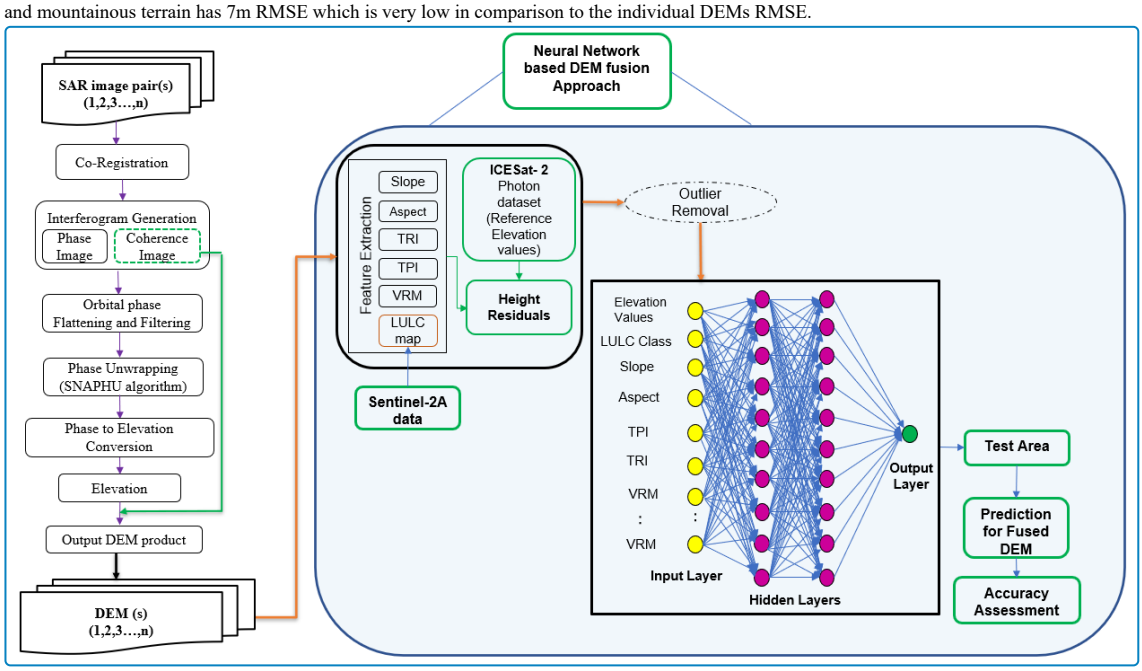
ABSTRACT

The Synthetic Aperture Radar (SAR) operating in the microwave portion of the EM spectrum provides an advanced technique of Interferometry (InSAR) for generating high-spatial-resolution DEMs. DEMs serve as an important input to a large number of topographic and modelling applications. Any improvement in the input using data fusion will add value to the output of these applications. The universal approximation and adaptive learning of the neural networks pave the way for developing a fusion framework for the improvement of these elevation models. The Feed-Forward Backpropagation neural network model is trained using training samples for different topographic terrains, one is Ghaziabad which is a plain area and the other is the Dehradun region which is a hilly terrain area. The elevation values from multiple input InSAR-based DEMs generated using Sentinel-1A/B images and values of DEM derivatives such as slope, aspect, topographic position index (TPI), terrain ruggedness index (TRI), vector roughness measure (VRM) are used along with Land Use Land Cover (LULC) classes information from Sentinel-2A multispectral data, for the preparation of training samples. The reference elevation used for training is obtained from the ICESat-2 ATL08 Land and Vegetation height product. By removing outliers and using hyperparameter optimisation for selecting the best fit neural network architecture, the models are trained. The plain terrain model uses a Log-sigmoid with a simpler structure while hilly terrain uses a linear activation function with more neurons in hidden layers. The trained models produce fused DEMs on the test areas and an accuracy analysis is performed. The root mean square error (RMSE) is estimated for evaluating the obtained fused DEMs with the TanDEM-X 90m DEM. A more complex mountainous terrain is selected from the north-eastern Himalayan portions of the Assam and Meghalaya region, where two ALOS PALSAR Radiometrically Terrain Corrected (RTC) 12m high-resolution DEMs are fused and improved using the neural network fusion framework. The fused output DEMs shows improvement with lower RMSE values as compared to the individual input DEMs. The plain terrain has 4.34m; hilly terrain shows 10.95m and mountainous terrain has 7m RMSE which is very low in comparison to the individual DEMs RMSE.



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