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A Review of Digital Elevation Model Super Resolution

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Abstract:
High-resolution (HR) digital elevation models (DEMs) have been found to be critical for many applications, as they provide accurate basic geodata, as well as more information and accurate results. However, despite the importance of HR DEM, many areas across the world, particularly in developing countries, lack access to them. Thus, researchers inspired by the success of super resolution (SR) on image enhancement, especially the use of deep learning (DL) approaches, instead of using high-precision equipment to obtain HR DEMs, have recently presented and are discussing the concept of DEM SR. This paper provides a review of such a DEM SR technique. It first explains the basic idea of SR, then describes DEM SR, and finally, a review of DEM SR algorithms proposed in the literature is presented, describing the main approaches and some of the shortcomings. This review shall provide the geoscientific community with information on an emerging alternative technique for acquiring HR DEM that is more cost-effective and can contribute to open data, which is widely recognised as the key engine for achieving the Sustainable Development Goals (SDGs).

Key Words: DEM, High Resolution, Low Resolution, Super Resolution, Machine Learning, Deep Learning.

I. INTRODUCTION

Digital Elevation Models (DEMs), as three-dimensional (3D) digital simulations of the Earth's surface through limited elevation data (Airbus, 2020; Jiao et al., 2020; Xu et al., 2019; Yan et al., 2021); are critical data tools in geoscience-related research and practical applications (Jiao et al., 2020; Yan et al., 2021); that have been widely applied in fields such as civil engineering (He et al., 2017), biology (Sankey et al., 2018), geomorphology (Garcia & Grohmann, 2019), hydrology (Vanthof & Kelly, 2019), and play an important role in surveying and mapping (Zhang et al., 2021).

Although global public DEM datasets such as Advanced Spaceborne Thermal Emission and Reflection Global Digital Elevation Model (ASTER GDEM), Alos World 3D (AW3D), and Shuttle Radar Topographic Mission (SRTM), among others, already exist and are widely used for different purposes, among other limitations, the spatial resolution of these public DEMs is low (Kubade et al., 2020; Yan et al., 2021); and DEM spatial resolution has been found to be critical for many applications because of the significant impact of DEM spatial resolution on computed topographic indices (Sørensen & Seibert, 2007) and the outcome of the analyses (Demiray et al., 2021; Nguyen et al., 2019), with high resolution (HR) DEM, in particular, providing accurate basic geodata (Xu et al., 2019), as well as more information and accurate results (Nguyen et al., 2019; Xu et al., 2019).

Nevertheless, despite the importance of HR DEM, many areas across the world, particularly in developing countries, lack access to HR DEM (Jiang et al., 2020). The reason is not unrelated to the fact that obtaining HR DEMs relies on the use of more precise instruments, which require more time and resources (Jiao et al., 2020). Thus, instead of using high-precision equipment to obtain HR DEMs, researchers, inspired by the success of super resolution (SR) on image enhancement, especially the use of deep learning (DL) approaches, have recently presented and are discussing a new concept, DEM SR (Xu et al., 2015), aimed at obtaining HR DEMs through the use of algorithms and related models to improve the resolution of existing low resolution (LR) DEMs, which is less expensive and more promising than developing high-precision instruments (Jiao et al., 2020).

Notwithstanding, studies on DEM SR are rare, but have been tested on different terrains across the world with varying experiences using different network architectures. However, the rising importance and needs for HR DEM with the rising spate of terrain related disasters such as floods across the world, the still high cost of directly acquiring HR DEM, and the increasing dominance of artificial intelligence and computer vision in today's data-driven world that have seen to the use of ML and DL algorithms application in solving all kinds of complex societal problems, we can only anticipate the continued development of the current DEM SR for many more years, thus justifying the evaluation of the present situation and the discussion of upcoming research needs and goals. more important than ever; often characterised by exaggerated expectations.

DL, which is a particular kind of machine learning (ML) algorithm inspired by the functionality of the human brain called neurons, which gave birth to the concept of Neural Network, can learns from data by itself. The goal is to approximate the mapping function such that when a new input LR DEM is provided, the HR DEM can be predicted.

So far, DL tools such as convolutional neural networks (CNN), generative adversarial networks (GAN), hopfield neural network (HNN) and recurrent neural networks (RNN) have played a crucial role in enhancing the resolution of LR DEM. Nevertheless, although depending on the fields of application, it is very important for SR to be highly accurate, as well as the computational time taken to produce such accurate output to be low and acceptable. The important thing about the SR process is modifying the original problem such that the solution is meaningful and close to the true scene while being less sensitive to errors in the observed images (Bannore, 2009). Even though image registration is generally the most critical step in various computer vision applications like medical imaging, remote sensing, target detection and SR imaging, among many more, (Bannore, 2009; Xiong et al., 2020), the accuracy, computational time and reliability of DEM SR to a larger extent depend on other factors like the network, the optimisers, activation function, the implementation platform and the processing unit.

This paper, therefore, aims at presenting a concise review of DEM SR, to address specific objectives (1) to determine the current state-of-the-art in DEM SR, and (2) to determine the drawbacks of current DEM SR. This review shall provide insights to the geoscientific community on an emerging alternative technique of acquiring HR DEM, which is more cost-effective and can contribute towards open data globally recognised as the key engine for achieving the Sustainable Development Goals (SDGs) (Gurin et al., 2015).

II. METHODOLOGY

To achieve the set aim and objectives, a systematic approach was adopted to search for all relevant articles published on DEM SR up to October 2022. This, therefore, involves a number of activities that include keyword selection, database selection and relevant literature search, literature sorting from different databases to identify duplicates, screening of literature for exclusion and inclusion in the review, analysis, and reporting of the review. To ensure all relevant studies are captured in this review, two main key words (super resolution and digital elevation model) were used to search three research bibliometric databases, comprising the two leading and competing citation databases (Scopus and Web of Science) (Zhu & Liu, 2020), and a database of peer-reviewed journal articles from various disciplines (Science Direct). Also, all synonyms of the two keywords determined from Scopus keywords finder were considered in the literature search in all the three databases using Boolean search techniques.

In Scopus, the keywords were searched in “Article title, Abstract, Keywords”, while in Web of Science and Science Direct, the same keywords were searched in “Advanced search”, and all the searches were equally conducted on the same day (29th October, 2022). The resulting literatures were collectively sorted, screened and selected using Excel. However, only peer-reviewed conference papers and journal articles totalling eighteen were finally considered. Figure 1 concisely presents the article selection process for this review.

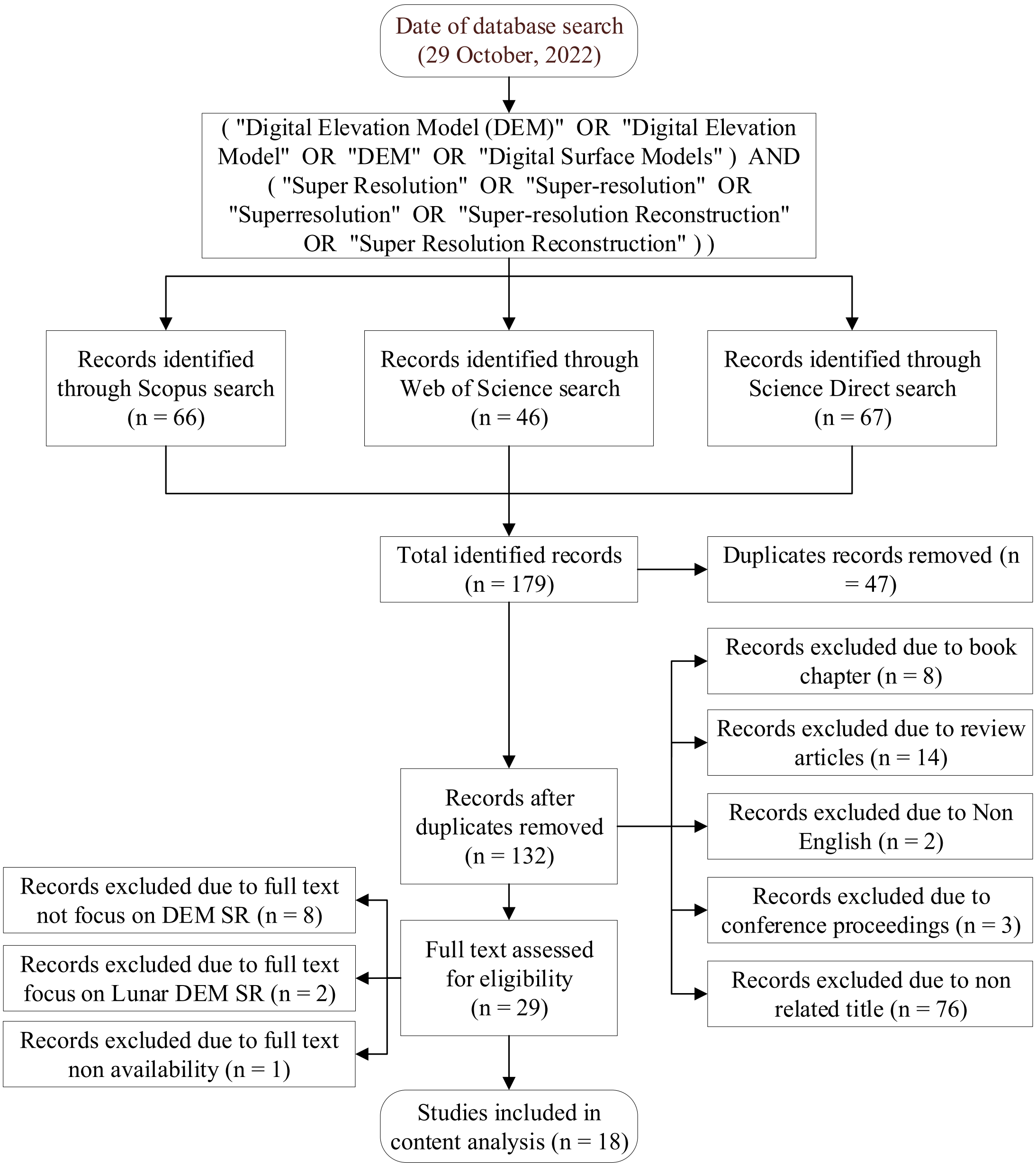

Figure 1. Summary of literature review process.

III. DIGITAL ELEVATION MODEL SUPER RESOLUTION

3.1 Super resolution principle and theoretical framework

SR is an old topic of research that has attracted a lot of attention in the field of computer vision since its introduction by Tsai & Huang (1984) to improve the spatial resolution of Landsat Thematic Mapper (TM) images with relative sub-pixel motion. It is a highly ill-posed task (Clabaut et al., 2021; Huang et al., 2017; Ledig et al., 2017; Zhang et al., 2019) that has developed into a research system after decades of development and advancement (Jiao et al., 2020). The basic idea behind SR is to create a visually appealing HR image from a single or multiple low resolution (LR) input images (Chen et al., 2016; Salvador, 2017).

The timeline of SR approaches includes early algorithms that are based on resampling (interpolation), the second-generation algorithms that rely on combining the information from multiple captures of the same scene (multiframe SR), and the modern algorithms based on machine learning (ML) models that exploit available examples (example-based SR) (Salvador, 2017). However, among the SR approaches, the learning-based approach has higher accuracy (Jiao et al., 2020), making it a popular topic of research in recent decades (Liu et al., 2021).

Nevertheless, the popularity of the learning-based approach based on different ML flavours in recent decades can be attributed to the numerical weakness of registration accuracy in multiframe SR, which limit resolution gains in most real-world cases; signal processing and statistics' data-driven trend; and the ML's large data handling and computational power, which enables the use of ML algorithms to learn patterns and models which provide an accuracy level that can't be matched by the traditional parametric models. In fact, the power of nonparametric ML models has positively impacted not just SR applications, but as well as other imaging and computer vision problems (Salvador, 2017).

However, because DEMs can be compared to images, with the planar coordinates and corresponding height values related to image pixels' positions and corresponding grey values, respectively (Chen et al., 2016; Demiray et al., 2020; Xu et al., 2015; Zhou et al., 2021), Xu et al. (2015), believing that the techniques in image SR can be used to improve DEM resolution, introduced the concept of DEM SR.

3.2 DEM Super Resolution

Like the conventional image SR, DEM SR, as introduced by Xu et al. (2015) with a nonlocal algorithm and the belief that multiple duplicate parts in a single DEM can be used as a reference, and further explored by Yue et al. (2015) by integrating data hole filling and noise suppression using a regularised framework for multi-source and multi-scale DEM fusion in 2015, aims at enhancing the resolution of a certain DEM based on its partial HR measurements obtained from some learning examples in order to minimise the cost of updating its resolution (Xu et al., 2015).

DEM SR can be achieved through interpolation, reconstruction, and a learning-based approach (Jiang et al., 2020; Zhou et al., 2021). However, performance of the interpolation approaches comprising of bicubic, bilinear, kriging and inverse distance weighting (IDW) interpolators, which normally fit the terrain surface using continually curved surfaces, varies across different terrains, with inconsistent accuracies (Chaplot et al., 2006; W. Z. Shi et al., 2005). While the reconstruction approach, which relies on data fusion to generate SR DEM by utilising complementary information in multi-sourced DEMs (Yue et al., 2015, 2017), imposes some extra assumptions like smoothness and limited bands, which heavily limit their performance (Zhang et al., 2019). Meanwhile, the learning-based approach can theoretically and practically improve the SR effect by learning some repetitive and similar patterns in original DEMs and incorporating such high-frequency information into SR versions of LR DEMs (Xu et al., 2015; Zhou et al., 2021).

However, inspired by the success of deep learning (DL) in image SR, particularly the effectiveness of the convolutional neural network (CNN) in image enhancement (Demiray et al., 2021), as demonstrated by Dong et al. (2014), some of the classic DL image SR models, which have shown good performance, have been used in DEM SR. DL is a branch of ML that aims to automatically learn data hierarchical representations and then leverage them to achieve the end goal, in which the entire learning process can be viewed as a whole (Yang et al., 2019). However, across many domains of artificial intelligence, including computer vision, DL has demonstrated significantly superior performance over other ML algorithms (Yang et al., 2019).

The main advantage of DL over other ML techniques is that nearly all aspects of the model are learned directly from the data, beginning with the lowest-level features that show a suitable representation of the dataset and progressing through the different layers of the network to provide higher-level abstractions for every specific problem (Salvador, 2017). Besides, because DL approaches could process massive amounts of geospatial data more efficiently and detect complex and diverse terrain features more accurately, they could be used to solve earth observation (EO) domain problems (Guo et al., 2020), including SR, which is currently an active area of research in EO image analysis (Clabaut et al., 2021).

IV. STATE OF DEM SUPER RESOLUTION RESEARCH WITH DEEP LEARNING

4.1 Processing steps

DEM SR typically involves four main steps. These include data pre-processing, model structure setting up, model training, and SR DEM generation and evaluation. The data pre-processing, which is generally the first step in any DL processing workflow, aims at preparing the input raw data into a format acceptable by the system. This consists of data preparation, cleaning, integration, normalisation, and transformation; as well as data reduction tasks, including feature selection, instance selection, discretisation, etc. The expected outcome of a credible data pre-processing task is to produce an accurate final dataset that is useful for subsequent processes (García et al., 2015).

The model structure setup involves choosing the appropriate model and its components, deciding on how it will look, and designing the algorithms in order to achieve the set objective. After duly setting up the model, the model is fed with relevant training data so as to learn from them. Thereafter, in order to generate the SR DEM, the model is fed with the test dataset. And finally, the accuracy of the SR DEM generated is evaluated accordingly.

4.2 Current studies and outlook

The use of SRCNN to reconstruct SR DEMs by Chen et al. (2016) was the first application of DL in DEM SR, and is a CNN-based approach, which can be considered an extension of SRCNN (Dong et al., 2014). In SRCNN, the SR problem is posed as a nonlinear image mapping problem. In this problem, a set of image features derived from convolutional filters must be mapped to pixel values for an image with a higher resolution. This can be accomplished by directly learning an end-to-end mapping between LR and HR images using a simple three-layer convolution structure, which makes the resultant image nearer to the natural image. Hence, the D-SRCNN developed by Chen et al. (2016) was a three-layer network designed to simulate human cognitive processes. The basic procedure of the D-SRCNN is network training, with the network trained on the basis of several DEM datasets and SR applications, which produces an HR DEM when an LR DEM is fed into the trained network.

Because of CNN’s proven effectiveness in high-dimensional data representation and function approximation (Lecun et al., 2015), and most importantly, because of CNN's local connectivity and shared weights that allow it to focus on features near as well as far from each other, consistent with the goal of function approximation in most problems of spatial analysis (Fischer, 1997; Zhu et al., 2019), D-SRCNN obtained better results relative to the bicubic method and was much more robust compared to the nonlocal similarity-based DEM SR (Xu et al., 2015). However, due to the three-layer simple convolution structure of the CNN and the fact that its performance depends largely on the number of layers, in which better performance is expected with more (deeper) layers (Shin & Spittle, 2019), improved CNN-based algorithms have been developed in order to improve accuracy and speed up the DEM SR training process.

Acknowledging the significant variation in depth values transition required for a DEM with scene types (e.g. urban scene need sharp transition whilst natural scene relatively smooth transition) after rescaling and the need for highly non-linear mapping function to understand the surrounding scene in order to recover a HR DEM, Shin & Spittle (2019) motivated by image SR with deep laplacian pyramid networks (LapSRN) (Lai et al., 2019), developed a deep SR network for DEM. Adopting a laplacian image pyramid but with much deeper structure implementation using multiple skip connections as well as additional Laplacian of Gaussian (LoG) based loss to restore the sharp depth discontinuities, the model tagged LoGSRN, which was experimented on DEMs from various satellite missions, demonstrated better performance relative to other standard SR models in terms of reconstructed DEM training convergence and Peak Signal to Noise Ratio (PSNR). However, the challenge of producing a higher scale DEM beyond x4 was identified, which suggests sequentially appending the LoGSRN as suggested in LapSRN as a possible solution.

Considering the complexity of urban topography due to human intervention, Jiang et al. (2020) presented an innovative multi-scale Mapping CNN (MSM-CNN) model, which reconstructed HR 0.5 m DEM of the highly urbanised city of London from LR 2 m, 4 m, and 8 m datasets resampled from a 0.5 m LiDAR DSM. The model, which was first trained using three small (25 km^2) areas with considerably different topographical features in the city’s rural, urban, and suburban regions, respectively, was later applied to successfully reconstruct the 0.5 m DEM over another larger (121 km^2) urbanised area containing mixed topographic features. Although visual, numerical, and vertical accuracy assessments reveal that the model outperformed all the interpolation methods, which generally provided a very limited level of improvement, particularly with the lowest (8 m) resolution urban DEM, with which restoring most of the topographic structures became impossible. Nevertheless, for better accuracy, the model requires that training data be representative of the typical features of urban terrain to be reconstructed, relatively cover a larger area, and be of higher resolution. But since acquiring larger coverage training data will inevitably increase the cost of obtaining sample datasets for the learning model training, leveraging a transfer learning technique was suggested as an alternative means of improving the model. Also, since NN down-sampling was relied on to generate the LR urban DEMs for implementing the proposed multi-scale reconstruction approach, which validates the MSM-CNN but raises the question of the effect of other down-sampling methods, collecting and using real LR datasets such as ALOS AW3D, NEXTMAP World 10, and WorldDEM where available, have been suggested to be explored to support the MSM-CNN's application in reconstructing HR DEMs in cities worldwide. Also, as it is quantitatively ascertained that the reconstruction accuracy of the MSM-CNN varies with slope ranges, land covers, and details of artificial buildings, the authors noted that considering land cover types by distinguishing different topographic features like roads, buildings, water surfaces, and natural terrains with comparatively high relief; terrain attributes like slope, curvature, or roughness; and urban semantic knowledge (rules of urban construction) such as transversal and longitudinal gradients of roads, in the model learning process so as to further enhance the model's performance deserves attention in future research. Also, while noting the probability of the numerical and morphological accuracy indicators presented in the proposed concept of morphological accuracy, having dimension difference and orders of magnitude, the authors suggested approaches combining the indicators using, say weighted sum for integrated assessment should be investigated further.

Other researchers, meanwhile, introduced transfer learning to the DEM SR problem. However, before the landmark work of bringing transfer learning into the DEM SR task proposed by Xu et al. (2019), Argudo et al. (2018) demonstrated how the use of supervised learning can improve the resolution of DEMs by adding details from corresponding HR orthophoto to terrain models. They achieved that by proposing a Fully Convolutional Network (FCN) architecture that, given a LR 15 m DEM and its corresponding HR 1 m orthophoto, produces a HR 2 m DEM with elevation data that reproduces both faithful (close to real) and plausible (realistic appearance) detail. The network, which was trained on HR 2 m ground-truth DEMs to learn the conversion of local orthophoto and terrain features into HR elevation data, consistently reduces the root mean square error (RMSE) with respect to HR height field by about 60% compared to the upscaled versions of the DEMs using bicubic and bilinear interpolation. However, because the model was tested using natural landscapes, the authors look forward to seeing the performance and optimisation of the model in the transition regions between natural and urban areas. Also, since HR orthophoto images were used in training the model, the authors see testing whether the use of hyper-spectral images can help with the SR enhancement as another avenue for the model's improvement. Finally, the authors also see the information of Digital Terrain Models (DTMs) along with Digital Surface Models (DSMs) wherever available as worth exploiting.

In their own effort, Xu et al. (2019) designed a deep gradient prior network that can recover effectively a more detailed HR DEM. The network involves two measures to address the challenge of obtaining sufficient HR DEM for robust network training for DEM SR. The measures include designing a deep CNN for the purpose of acquiring gradient prior knowledge, which can be used to estimate the studied DEM's HR gradient maps; and introducing transfer learning, which uses knowledge learnt from natural images to solve the DEM SR problem. This way, a CNN was pre-trained by the gradient of numerous HR natural images and then fine-tuned using the gradient maps of selected DEM training data. The HR DEM is then finally reconstructed using the estimated gradient maps as well as the original LR DEM. Several experiments demonstrated the feasibility of this approach and its superiority over the end-to-end SR algorithm, notably because of its ability to train a steady and converged network and ensure the robustness of SR with faster convergence speed, with an especially limited amount of HR data. However, the traditional CNN optimisation technique in the model, the model's weak ability to address DEM data with noise, accelerating the CNN training process, and increasing the network's robustness by acquiring additional DEMs as the training dataset, have been identified as some of the important issues that need to be resolved in the future.

While the issue of multisource data acquisition has been overcome by transfer learning (Xu et al., 2019), to increase the amount of DEM samples for model training and enhance the robustness of the CNN network, especially when acquiring enough DEM samples is impractical; Zhang et al. (2019) explored a simple but efficient way to obtain high-quality and HR DSM samples with LR image data. In their approach, a CNN-based SR method is first introduced into the conventional DSM generation process to enhance image resolution, followed by a pixel-level DSM generation process in order to achieve the aim of subpixel-level DSM generation. Although experiments and statistical results confirmed the feasibility and practicality of their proposed methods and their superiority to direct DSM upscaling under most terrain conditions, the authors considered that the result was new and advocated more experiments to demonstrate its practicality. Besides, while noting the likelihood of unknown errors during the reference DSM generation procedure affecting the model's output and that there was still room for the model's improvement, the authors suggested that reference in all their experiments be replaced by ground truth data and a new model which exploits actual degradations between corresponding HR and LR images is needed for improved performance.

Based on the premise that DEMs and remotely sensed images are all provided in a raster data model, Nguyen et al. (2019) explored the possibility of applying the Hopfield neural network (HNN) subpixel mapping approach developed for remotely sensed images to increase the detail and accuracy of DEMs through downscaling when no new subpixel-level measured data is available. Consequently, they developed a simple HNN that employs the spatial dependence maximisation as well as coarse elevation constraint functions for resampling a gridded DEM with a coarse resolution to generate a more finely gridded DEM that is more accurate in terms of surface representation than not just the original DEM but also finer grid DEMs generated by common resampling methods like bicubic, bilinear, and kriging interpolation. However, due to the linear activation function used in the HNN model for downscaling DEMs, there is a lack of tolerance in the constraint, like in the HNN for subpixel mapping. As a result, it is likely that any errors in the coarse DEM used as input will be completely transferred to the downscaled DEM. Thus, it was recommended that further study and modification of the model, particularly the activation functions, be conducted.

To further improve the accuracy of the reconstructed HR DEM obtained by existing DL methods, Jiao et al. (2020) considered deepening the convolutional layers and thus built a model based on a deep residual network to reconstruct the SR DEM. This was achieved by designing a neural network model composed of 30 convolutional layers, with each convolutional layer containing a rectified linear unit (ReLU) activation function in order to learn a feature mapping relationship between the LR and HR DEM. To avoid the network degradation due to an increase in the number of convolutional layers, they employed residual learning to accelerate the model's convergence speed, so as to realise the DEM SR process. The model, which was tested in the mountainous range of eastern China, showed that deepening the network remarkably improved DEM SR in terms of both visual effect and peak signal-to-noise ratio, compared to the use of fewer convolutional layers. Also, in comparison with the bicubic interpolation and CNN, the deep residual network produced a reconstructed DEM with more abundant details relative to the bicubic interpolation, and far less MAE and RMSE than both the bicubic interpolation and the CNN. However, considering their research has not been applied to coastal, urban, or other regions' DEM data, but scholars have gradually used DL technology to research in similar fields, the authors look forward to paying more attention to the application of their method in other areas, as they believe improvement of their model could achieve good results in urban and coastal areas. They also look forward to exploring mapping and feature extraction of their model in all kinds of geospatial and remotely sensed data in future works.

Motivated by feedback, neural networks for image SR (Zhen et al., 2019), Kubade et al. (2020) propose a recurrent neural network (RNN) architecture that learns to iteratively add high-frequency details to a LR DEM and converts it to a HR DEM without requiring any additional data or compromising its fidelity. Their methods involved upsampling of the LR DEM through bicubic interpolation and then using the proposed network to add high-frequency details. The network, which uses kernel sizes of 3x3 convolution layers and 1x1 compression layers, with all the Conv layers followed by the Parametric ReLU (PReLU) activation function, was implemented in PyTorch, and was designed in such a way that with each time step, the unrolled network reconstructs a new super-resolved (SR) output DEM while simultaneously storing the layer activations in a hidden state for use in the following time step demonstrated effective performance compared to FCN (Argudo et al., 2018) across different environmental settings, and showed better and more stable performance in all regions, including snow and densely vegetated areas. However, further efforts to improve learning from additional cues, such as spot heights, in sketches or break-lines instead of just LR DEM, have been suggested for more enriched feature-aware terrain by the authors.

Furthermore, nothing the poor performance of FCN (Argudo et al., 2018) in cases of heavy snowfall or dense vegetation not explored in DSRFB (Kubade et al., 2020), Kubade et al. (2021) inspired by attentional networks applied to applications such as image captioning, designed a module that allows the system to learns to concentrate and extract selective information in order to obtain a high fidelity super-resolved DEM with respect to the ground-truth terrain structures by selectively utilising information from other modalities such as aerial images. Interested in recovering lower-level details (alternately 'high frequency' details) such as edges, texture, sharp changes, cetera, they designed the attention network in a recursive manner and introduced part of the deep features back to the shallow layers as input, contrary to a typical CNN where features are captured by initial layers of the network. In the network, which they name Attentional Feedback Network (AFN), the feedback module's implementation is based on T T-state RNN, with the model refining the lower-level learned features by initial layers at each state to enable SR reconstruction at each time step. The overall network architecture is comprised of a Feature Extraction Module (FEM) consisting of two branches for geo-registered LR DEM and aerial image respective; an Attentional Feedback Module (AFM) that is the heart of the algorithm consisting of a stack of residual units and attention module; and a Reconstruction Block which takes in set of features from the AFM and fuse them to generate the interested higher frequency details which are added to input LR DEM directly through a global skip connection to predict super-resolved DEM..

In their own approach, Wu & Ma (2020), inspired by ESRGAN's success in image SR, instead of the typical resampling of the commonly used 30m resolution DEM for phase simulation in differential InSAR (DInSAR), which often causes phase residues and atmospheric effects of DEMs in the slope areas to be promoted and invariably affect the interpreted accuracy of InSAR results, developed a novel ERGAN based DEM SR technique to recover a HR DEM from an original DEM version. The two-step ESRGAN base model entails first pretraining an ESRGAN with a large number of natural images, based on which the learnt knowledge is transferred into the DEM problem, to then fine-tune the DEM SR network using small quantities of the LR SRTM DEM samples. The model, which is based on GAN, is composed of a feed-forward CNN with two convolutional layers, small 3×3 kernels, and 64 feature maps followed by a PReLU activation function as the generator network; and a discriminator network of 8 convolutional layers with 3 × 3 filter kernels and a LeakyReLU activation function to discriminate the original images and the reconstructed HR images. The network was implemented with the TensorFlow framework and trained using the NVIDIA GeForce RTX 2080 GPU and Google Colaboratory (a free GPU provided by Google). Nevertheless, the model, which successfully reconstructed a HR DEM with more details from the 30 m SRTM dataset, which was subsequently used as reference data to enhance slope deformation monitoring and improve the accuracy of InSAR estimation, outperforms previous DEM downsampling techniques such as bicubic and nearest neighbour in terms of sharpness and details. Similarly, quantitative analysis using indices like PSNR and Structural Similarity Index (SSIM) revealed that the ESRGAN-based method performed better than the traditional up-sampling methods. However, supplementing the model with multi-source information was acknowledged by the authors as a way that could achieve better SR DEM results.

However, recognising the mutual supplementation of multi-source data as a considerable way of achieving better DEM SR results, lacking in the ESRGAN-based method (Wu & Ma, 2020), Wu et al. (2021) created a real-world DEM SR dataset using LR and HR DEMs from SRTM and WorldDEM™, respectively, and referred to as the SW dataset. The ESRGAN model was adapted in an end-to-end manner to train on the SW dataset. Considering the misalignment real LR-HR pairs may suffer, they introduced the perceptual loss to improve the model's optimisation. Additionally, a logarithmic normalisation was proposed in order to compress the large elevation range and even out the distribution. And again, because the constructed SW dataset was insufficient for training the ESRGAN model from scratch, transfer learning was also introduced to train the model by first training the generator with a grayscale natural image dataset, and then the ESRGAN model was fine-tuned with the SW dataset and an adversarial mode of alternately training the generator and discriminator based on the pre-trained generator. The model, referred to as GAN-SW relative to other baseline methods such as Bicubic, GAN-S-BD, GAN-S-MD, GAN-W-BD, and GAN-W-MD, achieved the best performance with nearly 0.69 dB in PSNR and over 18.4% MSE improvement compared to the bicubic interpolation technique, which achieved the best performance of all baseline methods. However, because the model's feasibility was verified using SRTM and WorldDEM^{TM} data, exploring ways to generalise the proposed technique to more DEM datasets over wider regions has been highlighted by the authors.

Using a similar strategy employed by Chen et al. (2016) with the goal of enhancing a given DEM dataset spatial resolution up to four times without needing additional information, Demiray et al. (2021) showed that the techniques used in the single image SR can be used for DEM SR, by developing and evaluating a generative adversarial network (GAN) based model (D-SRGAN) to enhance the resolution of DEMs. The model's network design is composed of two opposing components (generator and discriminator), based on the SRGAN and EDSR models. The generator with twenty duplicate residual blocks created with two convolutional (3 × 3 kernel and 64 feature maps) layers and a ReLU activation layer in between accepts LR DEM to produce HR DEM. The discriminator with nine convolutional (3 × 3 filter kernels and 512 feature maps) layers, each followed by a Leaky RELU activation function, takes fabricated or real HR DEM as input and predicts the origin of the input. Despite demonstrating promising results in constructing a nearly 1m DEM from a 15m DEM, the model, which was implemented on PyTorch, was unable to perform consistently across terrains, producing more realistic results in flatter terrains than steeper ones. Thus, using different metrics in the generator's training phase, such as slope, experimenting with different losses, developing variational autoencoders to find a better architecture for minimising slope errors between flatter and steeper terrains, examining the effects of generated high-resolution DEMs on various tasks, and comparing the results to real high-resolution DEMs have been identified as potential open questions.

Inspired by CNN's excellent performance in SR image analysis, Zhou et al. (2021) explored using deep residual neural networks to generate HR DEMs from LR DEMs. Thus, they proposed an enhanced double-filter deep residual neural network (EDEM-SR). The network is composed of a feature extraction module with a convolution layer for extracting the LR DEM input data features through the convolution layer and outputting feature maps; the residual module with ReLU activation functions for increasing the depth of the network, and further extracting and fusing the feature maps generated by filters with different receptive fields; and an up-sampling module consisting of a convolution layer and a sub-pixel convolution layer for enlarging the size of the output image. The EDEM-SR network, which was implemented based on the Pytorch framework on the GeForce GTX 2080 GPU equipped with 16 GB of memory, achieves DEM SR by extracting and fusing features using different receptive field sizes to reconstruct a more realistic HR DEM. Compared to bicubic, bilinear, and EDSR methods, EDEM-SR reconstructed DEMs better matched the original DEMs and showed lower mean absolute error (MAE) and RMSE. However, the model is limited by its inability to train SR mapping models at any scale, an increase in computational amount and consequent reduction in computation efficiency, the requirement for training of separate models for different types of terrain, and its focus on the overall terrain characteristics without considering the HR terrain feature points of local areas. Thus, constraining the SR DEM to retain more terrain features by training terrain features into the network, incorporating open-access LR DEMs instead of just downsampling HR DEMs to generate training data, has been highlighted as a future research direction.

Finally, Zhang et al. (2021) applied the efficient sub-pixel convolutional neural networks (ESPCN) (Shi et al., 2016) to the DEM SR problem and improved it by adding the "zero" boundary method as a data pre-processing technique, which improves its accuracy and convergence. Consequently, they propose recursive sub-pixel convolutional neural networks (RSPCN) to construct HR DEMs. The network is composed of three sub-networks: the embedding sub-network for feature map generation from LR DEM, the recursion sub-network for finishing the SR, and

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the reconstruction network for generating the HR DEMs. The proposed method is similar to an interpolator that over-samples the DEM, which begins with a single image and ends with the same single image but with a finer pixel density. The model, which was trained on the Tensorflow platform and experimented with six archetypal landform datasets derived from 3DEP LiDAR sources, that have typical terrain characteristics such as eroded plateau, active sand dunes, volcanic caldera, braided riverbed, shield caldera, and stabilised sand dunes; in comparison to the SRCNN method, showed speed up in the feature extraction process because of the dealing with sub-pixel convolution layers recursively in the RSPCN method. Also, when compared to other traditional interpolation methods (bicubic, bilinear, nearest-neighbour), the RSPCN reduces over-smoothing and improves accuracy. And relative to the ESPCN, the RSPCN introduces a recursive idea and reduces network depth. The results indicate that it is particularly useful for visualisation applications such as real-time terrain simulations and realistic terrain rendering. However, addressing and analysing further the effects of the varied data pre-processing techniques is highlighted as a focus for future work.

To solve the inverse problem of DEM SR reconstruction, making full use of the DEM a priori information, (Lin et al., 2022) based on the presence of a substantial amount of repetitive information within a DEM, a new DEM SR reconstruction approach is proposed based on the complementary relationship between externally learned SR reconstruction methods and internally learned SR reconstruction methods. Using the internal learning method to learn the DEM internal prior, a LR detailed features-rich dataset of the DEM is generated, and based on this, a constrained external learning network is trained for the discrepancy data pair.

Zhang et al. (2022) propose the terrain feature-aware superresolution (TfaSR) model for DEM SR. The model which is composed of three modules which includes the deep residual module that effectively extract deep terrain features from DEM elevation patterns, the adaptive terrain feature extraction module which accept the extracted feature maps by the deep residual module to further recognizes and extracts multi-size terrain features in order to achieve trade-off between accuracy and efficiency using deformable convolution, and finally a collaborative lose module which refines global accuracy as well as local terrain features for effective terrain feature recovery.

4.3 Summary of current studies on DEM super resolution.

The DEM SR models developed thus far are based on few DL networks, use in conjunction with few other important components such as the activation function, optimization algorithm and equally implemented in few platforms. Table 1 presents concisely the various DEM SR models, the DL networks adopted in their design, and other important components such as the activation functions, optimization algorithms, platforms used for their implementation, and their strengths and weaknesses. Also, Figure 1 depicts the percentages of studies that use the respective networks, activation functions, optimization algorithms, and implementation platforms.

Table 1. Summary of DEM SR models and their components

Model	Network	Activation function	Implementation platform	Optimizer	Strength	Weakness	Reference
Nonlocal algorithm					◦ can preserve details without introducing artifacts ◦ can achieve higher accuracy than the traditional interpolation techniques	◦ Difficulty in finding similar patches in terms of rotation and scale to increase the chances of obtaining similar patches, ◦ Time consumption of the searching process ◦ Different learning	Xu et al. (2015)

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Model	Network	Activation function	Implementation platform	Optimizer	Strength	Weakness	Reference
						data will result in different SR	
Regularized super-resolution					◦ Considered factors such as datum differences, random noise, scaling effects, and horizontal or vertical inaccuracies among multi-scale DEM products. ◦ Reconstruct the required data with the highest resolution and comprehensive coverage of the input data	◦ overlooked more complex issues like other unpredictable production errors ◦ overlooked the effect of cartographic generalization	Yue et al. (2015)
Convolutional neural network based DEM super-resolution	CNN	ReLU			◦ Achieved better results compared to the bicubic technique ◦ More robust than the nonlocal similarity-based DEM SR	◦ Shallow (three-layer) convolution structure ◦ Network trained on the basis of lots of DEM datasets	Chen et al. (2016)
Fully Convolutional Network for synthesizing detail on DEMs	CNN	ReLU	Caffe Library	Adam optimiser	◦ Transfer learning ◦ uses skip-connection for features combination at different scales	◦ limited testing site	Argudo et al. (2018)
LoGSRN: Deep Super Resolution Network for Digital Elevation Model	CNN	PReLU		Adam optimiser	◦ multiple recursive feedback and feedforward skip connections ◦ Laplacian of Gaussian (LoG)-based loss function	◦ Can't producing higher scale DEM beyond x4	Shin & Spittle (2019)
DEM super-resolution	CNN	ReLU	Python 3.6 and	Adam optimiser	◦ deeper convolutional layers	◦ limited testing site	Jiang et al. (2020)

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Model	Network	Activation function	Implementation platform	Optimizer	Strength	Weakness	Reference
based on a deep residual network			Tensorflow 1.12		◦ residual learning ◦ can handle large abrupt elevation changes		
Deep gradient prior network for DEM Super Resolution	CNN	ReLU	Pytorch	stochastic gradient descent (SGD) and mini-batch gradient descent	◦ deep CNN ◦ Transfer learning ◦ Can train a steady and converged network ◦ Faster convergence speed with limited amount of HR data	◦ traditional CNN optimization technique ◦ Weak ability to address DEM data with noise ◦ Slow training process.	Xu et al. (2019)
CNN-Based Subpixel Level DSM Generation Approach via Single Image Super-Resolution	CNN		Caffe library		◦ rational polynomial coefficient regeneration	◦ unknown elevation deviation in forested terrains	Zhang et al. (2019)
Deep residual network	CNN	ReLU	Python 3.6 and Tensorflow	Adam optimiser	◦ 30 convolutional layers ◦ Residual learning ◦ High performance in mountainous area	◦ Not tested on DEM of coastal, urban or other areas.	Jiao et al. (2020)
DEM Super-Resolution based on Feedback Network (DSRFB)	RNN	PReLU	Pytorch	Adam optimiser	◦ Stable performance in all regions, including snow and densely vegetated areas.	◦ Learn from just LR DEM	Kubade et al. (2020)

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Model	Network	Activation function	Implementation platform	Optimizer	Strength	Weakness	Reference
					◦ Iterative learning		
ESRGAN-based DEM SR method	GAN	Leaky-ReLU, PReLU and sigmoid	Tensorflow	Adam optimiser	◦ Transferred learning ◦ faster convergence speed		Wu & Ma (2020)
Real-world DEM SR	GAN	Leaky-ReLU and Sigmoid		Adam optimiser	◦ perceptual loss ◦ Logarithmic normalisation	◦ only SRTM data was used	Wu et al. (2021)
DEM Super-Resolution with Generative Adversarial Networks (D-SRGAN)	GAN	Leaky-RELU and PReLU	Pytorch	Adam optimiser	◦ Good performance in flat terrains	◦ Inconsistent performance across different terrains ◦ Poor performance in stepper terrains	Demiray et al. (2021)
An enhanced double-filter deep residual neural network (EDEM-SR)	CNN	ReLU	Pytorch	Adam optimiser	◦ Different receptive fields sizes ◦ Good performance in mountainous terrain ◦ Reduction in computation efficiency	◦ Inability to train SR mapping models at any scale ◦ increase in computational amount ◦ Training of separate models for different types of terrain	Zhou et al. (2021)
Recursive sub-pixel convolutional neural networks (RSPCN)	CNN	ReLU	Tensorflow	Adam optimiser	◦ The sub-pixel level processing ◦ Fast feature extraction process ◦ Reduces over-smoothing ◦ Recursive ideas		Zhang et al. (2021)

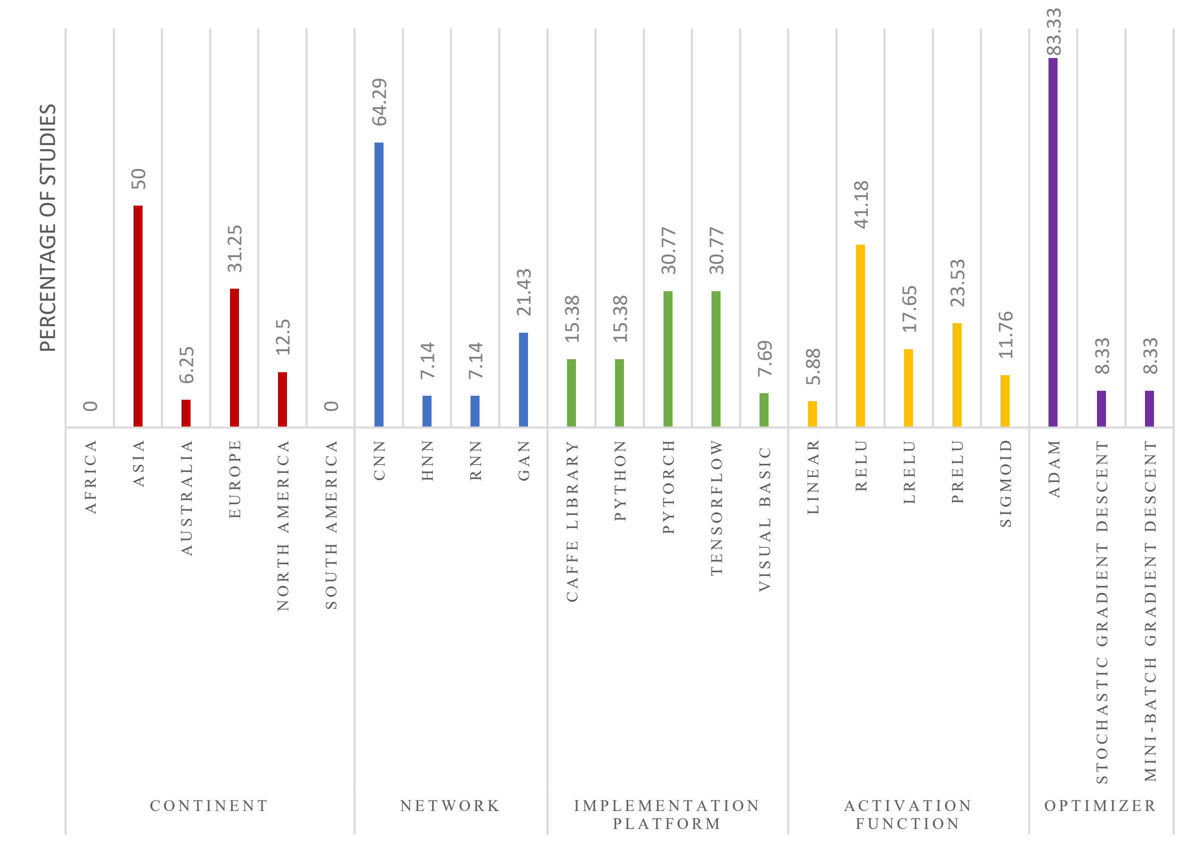

Figure 1. Overview of DEM super resolution models' studies

The network adopted in designing a DL model is critical to the functionality of the model. The networks are the mathematical models used in solving the SR problems using unstructured data. These mathematical models consisting of neurons, are divided into layers such as input layers, hidden layers, and output layers. The different networks that the various DEM SR models have been based on are briefly described with the pros and cons in Table 2.

Table 2. An overview of networks used in DEM SR models

Network	Description	Strength	Weakness	References
Convolutional Neural Network (CNN)	a type of feedforward neural network computational model that uses a variation of multilayer perceptrons containing one or more entirely connected or pooled convolutional layers.	- offer very high accuracy in image recognition problems - capable of automatically detecting important features without any human supervision - weight sharing which reduces the networks complexity - parameter Sharing - Operate on Fixed Length input - can handle spatial Relationships - can deal with high dimensional data	- do not encode object position and orientation. - lack the ability to be spatially invariant to the input data - require lot of training data in order to work efficiently	(Dong et al., 2014)

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Network	Description	Strength	Weakness	References
Recurrent Neural Network (RNNs)	a type of neural network in which node connections can form a cycle, allowing output of processing nodes to be fed back into the same node (and thus do not pass the information in one direction only) and the model to demonstrate temporal dynamic behaviour.	- suitable for sequence data - remembers each and every information through time - Long Short term Memory, which makes it useful in time series prediction - parameter Sharing - recurrent connections	- gradient vanishing and exploding problems - difficult to train - cannot process very long sequences if using tanh or ReLU as an activation function - no spatial relationships	(Mandic & Chambers, 2001)
Hopfield Neural Network (HNN)	a fully interconnected, single-layer, autoassociative, nonlinear, discrete or continuous-time network.	- can be used for various pattern recognition problem - total recall from incomplete or partial data - stability under asynchronous conditions - easy implementation in hardware - fault tolerance - content addressable memory	- can rest in a local minimum energy state rather than a global minimum energy state.	(Hopfield, 1982)
Generative Adversarial Network (GAN)	a type of neural network in which two neural networks (the generator and the discriminator) compete against each other in a zero-sum game where one agent's gain is another agent's loss, to generate desired data.	- go into data specifics - learns data internal representations, however messy or complicated the distributions - generate data that resembles the original data - can easily interpret data into different versions - can be trained with unlabeled data	- difficult to train - mode collapse - vanishing gradients problem	(Goodfellow et al., 2014)

Another important component of the DL model is the activation function. This is the mathematical equation which determines the output of the model. The activation plays a significant role in the network's ability to converge and the rate of convergence, or in some instances, prevents neural networks from ever converging. The activation function also aids in the normalisation of any input in the range of 1 to -1 or 0 to 1. Nevertheless, Table 3 presents a concise summary of the various activation functions that have been used in DEM SR models.

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Table 3. An overview of activation functions used in DEM SR models

Activation Function	Description	Strength	Weakness
Linear	a simple, straight-line function in which the activation varies in proportion to the input. The output of linear activation function is always in the range (-∞,∞), but not zero centred.	- can handle multiple classes - convex error surface for faster optimisation	- can't be defined in a particular range - constant gradient that doesn't depend on input - no tolerance in the constraint - error change rate during backpropagation is constant - with constant gradient, neural network will not truly improve
Rectified linear unit (ReLU)	an unbounded, nonlinear or piecewise linear function that directly output positive inputs, or output 0 if the input is negative.	- simpler computation - capable of producing a true zero value - Neurons are not simultaneously activated. - high performance in non-linear fitting - suitable for supervised tasks on large labelled data sets - less tendency for gradients to vanish during training - allow models to learn faster and perform better	- problem of dying neurons - instability in the learning - can't handle sudden changes
Leaky RELU	an improvised ReLU that addresses the problem of dying neurons in ReLU by giving some partial value (0.01 instead zero) in the negative axis	- addresses the problem of dying neurons in ReLU - enable back propagation for even negative input values	- inconsistently negative input values prediction - can overshoot, killing neurons during front propagation if learning rate is set very high
ParametricRelu (PReLU)	an improved Leaky ReLU that addresses the problem of dying neurons in ReLU by fine-tuning the activation function based on its learning rate (instead of giving some partial value in the negative axis like in Leaky ReLU	- solve the problem of gradient's becoming zero - might adopt to sudden changes using backpropagation	- perform differently for different problems - doesn't solve exploding gradient problem
Sigmoid	a non-linear, continuously differentiable, bounded, real functions with non-negative derivative at every point and are defined for all real input values. The output of sigmoid function will always be in the range (0,1), but not zero centred.	- provides Smooth gradient which assist in preventing "jumps" in output values - bounding output values between 0 and 1, helps in normalizing the output of all neurons - provides clear predictions of very close to 0 or 1 which	- prone to vanishing Gradients Problem - prone to exploding gradients - range compression due to nonlinearities

Activation Function	Description	Strength	Weakness
		helps in improving model performance.	

see, (Sharma et al., 2020)

V.CONCLUSION

Although SR is an old technique, its uses for DEM resolution enhancement are fairly recent, having commenced in 2015 with the work of Xu et al. (2015). Research in the field of DEM SR has been greatly encouraged by the development of DL, and is still evolving with numerous areas of improvement around the algorithms' sophistication to speed up their performance and increase the accuracy and reliability of their outcome, which have all been highlighted in this paper. However, if reliable and accurate HR DEMs can be generated through DEM SR, it shall save time and cost, and above all, it promote access to HR topographic information, which can help in addressing the challenging issue of data scarcity and have far-reaching implications in a variety of water-related applications, especially in many developing countries where water related disasters are threatening the capacities of countries' to achieving the Sustainable Development Goals (SDGs), especially goal 11 (Sustainable Cities and Communities), and particularly target 11.5 aimed at reducing tremendously the number of deaths and people affected by water-related disasters.

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