Applications of AI/ML Methods on Meteorological Data

B.E. Project Report

Submitted in partial fulfillment of the requirements

For the degree of

Bachelor of Engineering

in

Computer Engineering

by

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CERTIFICATE

This is to certify that, the project titled

" Applications of AI/ML Methods on Meteorological Data "

is a bonafide work done by

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and is submitted in the partial fulfillment of the requirement for the degree of

Bachelor of Engineering
in
Computer Engineering
to the
University of Mumbai

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Abstract

Some vital services, such as roads, ecological systems and power plants, feel the impact of climate change. However, modern Earth System Models (ESMs) are performed at too large spatial resolutions to determine the localized impacts. Local scale estimates can be made using statistical downscaling, a method that uses historical climate measurements to learn a low-resolution, high-resolution mapping approach. The spatial-temporal nature of the climate system encourages the adaptation of super-resolution image processing techniques to statistical downscaling. Super Resolution Convolution Neural Network in which SR methods, based on a low resolution (LR) image, are designed to accurately estimate a high resolution (HR) image. As presented by Dong et al, the CNN architecture can be designed to learn functional mapping between LR and HR using three operations, patch extraction, non-linear mapping, and reconstruction.Deep learning based approach can be used as an alternative to traditional downscaling methods using the SRCNN model. By inserting factors that influence the variable in the SRCNN model, e.g. Rainfall variable with elevation data can generate better downscaling projections.On Indian Meteorological Data (IMD data), We provide statistical downscaling approaches in daily rainfall data from 1 degree (100 km) to 1/4 degree (25 km) across the Indian region.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The recent phenomenal interest in convolutional neural networks (CNN) must have led to the exploration of its inevitable potential for the Super-Resolution. Method directly learns an end-to-end mapping between low / high resolution images [1]. Mapping is known as the SR convolutional neural network (SRCNN) that takes the low-resolution image as input and produces high-resolution output. However, unlike conventional methods that treat each part separately, this approach optimizes all layers together. CNN has a lightweight frame, but it does demonstrate more state-of-the-art quality and results in restoration.

1.1 Overview

The SRCNN has several appealing properties.First, its structure is intentionally designed with simplicity in mind, but offers superior precision compared to state-of-the-art approaches. In only a few training iterations, the Super-Resolution Convolution Neural Network (SRCNN) surpasses the bicubic standard and, in modest preparation, exceeds the sparse-coding system[1]. More training iterations may further improve performance.

1.2 Objective

The objectives are:-

- To generate high resolution meteorological data using DeepSD and SRCNN
- To show that DeepSD is better compared to SRCNN and linear interpolation for super resolution applications on meteorological data

1.3 Motivation

The lack of explicit spatial models in the Statistical Downscaling of Earth System Model's motivated the study of the applicability of computer vision approaches, most often applied to images, to this problem. More specifically, progress in single-image super-resolution (SR) corresponds well to SD, which learns mapping between low-and high-resolution images. The aim is to provide downscaled climate projections to areas without high-resolution observations through what can be thought of as transfer learning. The topic will be discussed further in Section 4 (Proposed Work). Super-resolution Convolution neural networks have also been able to capture spatial information in meteorological data to improve traditional downscaling methods.

1.4 Organization of the report

- The Chapter 1 contains objective and motivation of the entire project and it gives the general overview of our project
- The Chapter 2 includes literature survey tells us about the existing system
- The Chapter 3 contains the proposed work in terms of its framework and methodologies used, hardware and software requirements
- Chapter 4 illustrates the entire schedule of the work to be done
- Chapter 5 gives the detailed flow diagrams which help to understand the flow of the systems working
- Chapter 6 shows the Results and required validation

Chapter 2

Literature Survey

Convolutional Neural Networks are very similar to ordinary Neural Networks consisting of neurons with learnable weights and biases. Each neuron receives certain inputs, performs a dot product and potentially applies non-linearity to it. The whole network still expresses a single differentiable score function: from raw pixels at one end to class scores at the other end. And they still have a loss function (e.g. SVM/Softmax) on the last (full-connected) layer. Factors favoring usage of CNN-

1. Efficient training on modern GPUs
2. (ReLU) which makes convergence much faster
3. Easy access to an abundance of data

Figure 2.1: SRCNN on Images [1]

A classic issue in computer vision is the single image super-resolution (SR), which attempts to recreate a high-resolution image from a single low resolution image [3]. This problem is potentially ill-posed because there are a multiplicity of solutions for any given low-resolution pixel. Such a problem is usually mitigated by clear prior knowledge limiting the solution space. Latest state-of - the-art approaches primarily follow an example-based approach for learning the objectives. These methods either exploit internal similarities of the same image, or learn from external low- and high- pair mapping functions.The external example-based methods can be developed for super-resolution of a generic image or can be built to fit different domain tasks, i.e., face hallucination according to the training samples provided.

Name of Paper	Author, year	Method	Accuracy
Image Super-Resolution Using Deep Convolutional Networks	Chao Dong,2015	SRCNN	89.99
Application of Super-Resolution Convolutional Neural Network for Enhancing Image Resolution	Kensuke Umehara , 2017	SRCNN	86.55
Cascade Trained and Trimmed Deep Convolutional Neural Networks for Image Super Resolution	Haoyu Ren , 2016	CNN	84.55
Generating High Resolution Climate Change Projections through Single Image Super-Resolution	Thomas Vandal , 2017	SRCNN , DEEPSD	84.55

Table 2.1: Review of Literature Survey

2.1 Survey of Existing System

1. Image Super resolution using deep convolution networks[1] :
   The proposed method has shown that typical sparse coding methods can also be viewed as a deep convolutional network. Unlike conventional approaches that handle each individual node, there approach optimizes all layers together. DeepCNN has a lightweight framework, but is state of the art in restoration and delivers fast acceleration for practical online use.[1]

2. Generating High Resolution Climate change Projections through single Image Super Resolution [2]:
   The spatial nature of the climate system encourages the adaptation of super-resolution image processing techniques for statistical downscaling. DeepSD , a generalized stacked super resolution convolutional neural network (SRCNN) framework with multi-scale input channels for statistical downscaling of climate variables was proposed [2].

3. Application of Super Resolution Convolution neural network for enhancing image resolution [4]:
   The super-resolution convolutional neural network (SRCNN) scheme has been implemented and tested using the post-processing technique, which is the latest deep-learning based super-resolution method for enhancing image resolution in chest CT images. The image restoration efficiency of the SRCNN was substantially higher than that of the linear interpolation methods($p < 0.001$ or $p < 0.05$).The high-resolution image recovered by the SRCNN method has been strongly restored and comparable, in particular, to the original reference image for a 2x magnification [4].

4. Cascade Trained and Trimmed Deep Convolution Neural Networks for image super resolution [5]:
   A cascade-based training technique is suggested to enhance the accuracy of the neural network while slowly increasing the number of layers. One-shot trimming and cascade trimming are used. The size of the network is gradually reduced layer by layer without a significant loss of discriminatory cascading capacity of the network [5].

Chapter 3

Project Proposal

Conventional techniques require high-resolution observational data, which means that regions with little observation data, often the poorest regions most affected by climate change, are unable to receive the low-level climate data needed for adaptation. The lack of clear spatial models in the Statistical Downscaling of Earth System Models has led us to investigate the use, most frequently used for images, of computer vision approaches to this issue. In order to solve this problem, Advances in single-image super-resolution (SR) correspond well to SD, which learns to map between low and high-resolution data.

The spatial-temporal nature of the climate system encourages the adaptation of super-resolution image processing techniques to statistical downscaling [2]. In our work, a generalized super resolution convolutional neural network (SRCNN) framework with multi-scale input channels for statistical downscaling of climate variables.The aim of this approach is to achieve a very high-quality super resolution image that would be used to make localized climate projections similar to the application of statistical downscaling.

3.1 Proposed Work

In this project, aim is to apply SR model on IMD data for statistical downscaling.The CNN architecture can be designed to learn functional mapping between low resolution (LR) and HR using three operations,

- Patch extraction:
  Extract patches from the low-resolution and high-dimensional vector.
- Non-linear Mappings:
  Mapping of each high-dimensional vector onto another high-dimensional vector.
- Reconstruction:
  Reconstruction of HR image with sub patches.

3.2 Proposed Methodology

Statistical downscaling is the problem of mapping a low-resolution climate variable to a high-resolution projection. The work focuses on the statistical downscaling of 'Indian Meteorological Data' which shows that SRCNN is better than the conventional model. DeepSD, which includes additional parameters that affect the variable in order to generate better high resolution projections. Short descriptions of these methods are provided below

3.2.1 Super- Resolution CNN:

Given a low resolution (LR) image, SR methods aim to accurately estimate the high resolution (HR) image. As presented by Dong et al. [1], the CNN architecture can be designed to learn functional mapping between LR and HR using three operations, patch extraction, non-linear mapping, and reconstruction.[1] The LR input is X while the HR label is Y. A three-layer CNN is then designed to produce a high-resolution estimate. Convolutions in layers 1, 2, and 3 are found to decrease the size of the image depending on the filter sizes chosen, f1,f2, and f3. During the test period, padding using the replication method is used before the convolution operation to ensure that the size of the prediction and the ground truth correspond. During training, the labels are cropped in such a way that Y and F (Xi), without padding, are of equal size.

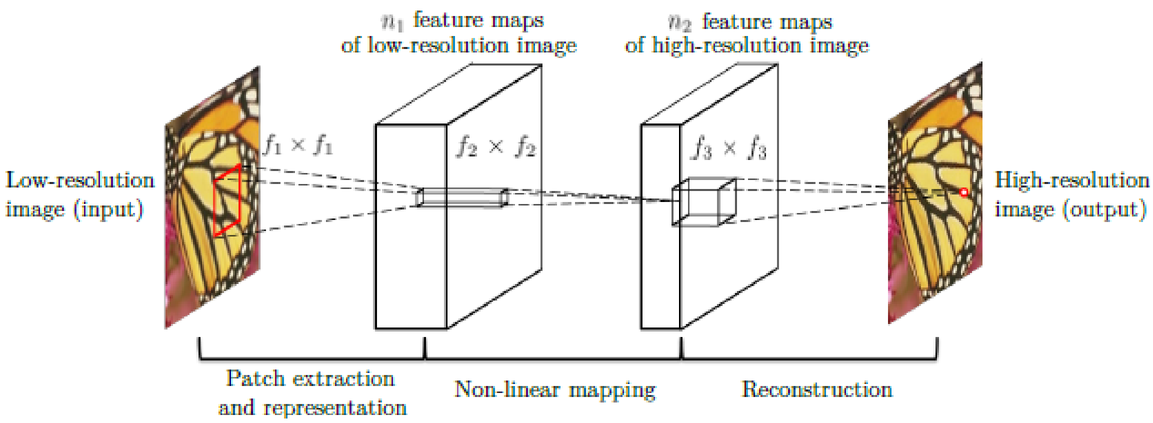


Figure 3.1: Operations in SRCNN [1]

3.2.2 DeepSD:

DeepSD, the enhanced and special architecture of the SRCNNs, as a novel statistical downscaling technique. In general, when applying SR to images, only the LR image is used to estimate the HR image. However, during statistical downscaling, the underlying high-resolution data may coincide with this LR image in order to estimate the HR images. For example, we have two types of inputs, including LR precipitation and static topographical features, such as HR elevation and land/water masks, to estimate HR precipitation and downscaling precipitation. Since topographical characteristics are considered forehand at very high resolution and usually do not alter during the time of interest, they can be leveraged at each scaling factor. Rainfall event and various resolution improvements.

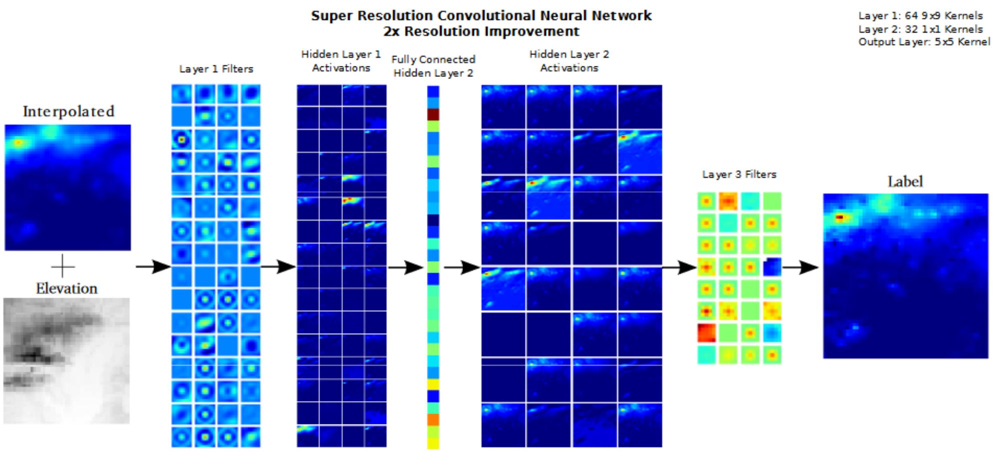


Figure 3.2: Visualization of DeepSD [2]

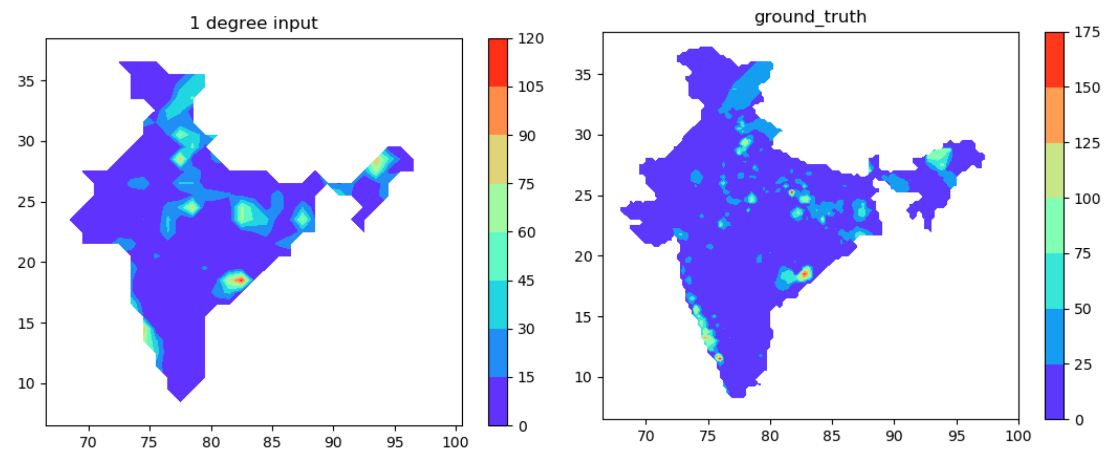
3.2.3 Details of data and its processing

Meteorological data is generally for a specific or multiple parameter. GRIB (Gridded Binary or General Regularly Distributed Information in Binary Form) is a concise data format used in meteorology to store historical and weather forecast data [6]. Similarly, other meteorological data, such as netCDF, PNT, are similar to GRIB files and need to be pre-processed.

Data used in this work:

- 1 degree (100km):
  size is 33x35 - (Input).

- 0.25 degree (25km):
  size is 129x135 - (Label).



(a) Input (1 degree data) (b) Ground Truth (0.25 degree data)

Figure 3.3: Visualization of different formats IMD data

- Data Preprocessing

The data for a single day at the highest resolution, 0.25 for INDIA, is a ”image” of the size 129x135 [7]. Images are obtained at each resolution by up-sampling using a bilinear interpolation [8]. For example, upsampling to 1 degree reduces the size of the image from 129x135 to 33x35. Rainfall features for the first SRCNN, downscaling from 1 to 0.25, are first up-sampled to 1 and then interpolated to 0.25 for the second time in order to match the output size of 129x135. Subsequently, this process is applied to each SRCNN according to its corresponding resolution. During the training phase, 35x35 sub-images are extracted at a time of 23 to provide heterogeneity in the training set. The number of sub-images per year (23,360) increases with resolution. Rainfall values are only available on land. Convert all values excluding land values to ’NAN’ and then the data is interpolated to obtain INPUT data. Each ’NAN’ value is converted to a sufficiently low ’0’ value, which is then masked after downscaling.

3.3 Details of Hardware Software Requirements

3.3.1 Hardware Requirement

- Minimum RAM - 8GB
- Processor - Minimum Intel i5(7^{th} generation) or better
- Graphics Card - 4GB
- Storage - 8GB or more

3.3.2 Software Requirement

We will be using the Python language for building the model and some of the libraries utilized will be

- Scikit-learn
- Numpy
- Pandas
- Matplotlib (for Visualization)
- Keras (for CNN)

The entire process of Data preprocessing, Data visualization, Building the CNN model and Inference of the model will be done in python.

Chapter 4

Planning and Formulation

4.1 Schedule for Project(Gantt Chart)

	Task	Start	End	Dur
	BE Project	7/1/19	4/9/20	195
1	Abstract Presentation	7/1/19	7/20/19	14
2	Literature Survey	7/20/19	8/16/19	20
3	Problem Definition	8/26/19	8/30/19	5
4	Proposed Methodology	8/30/19	9/21/19	15
5	System Requirements	9/21/19	10/1/19	7
6	Design of Proposed System	10/1/19	11/1/19	23
7	Implementation Details	11/1/19	2/24/20	76
8	Coding	11/1/19	2/28/20	80
9	Testing	2/28/20	3/15/20	11
10	Cost and Benefit Analysis	2/24/20	3/18/20	18
11	Result Analysis and Testing	3/18/20	3/27/20	8
12	Report Writing	3/27/20	4/9/20	10

2019 2020
Jul Aug Sep Oct Nov Dec Jan Feb Mar Apr

Figure 4.1: Gantt Chart

4.2 Flowchart For Training a model

The train.py file is intended to train the model that follows the flowchart shown in Figure 4.2.

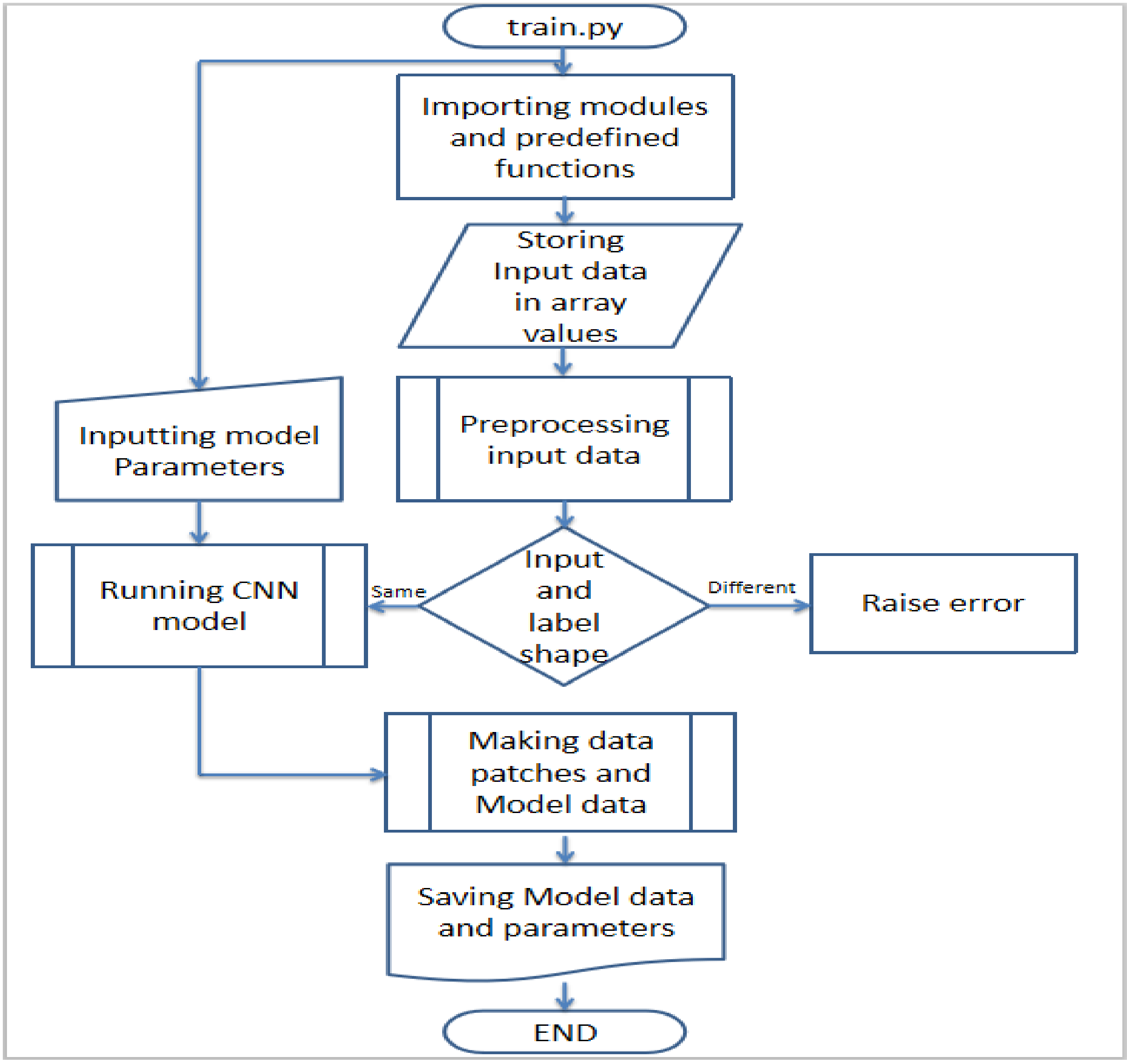


Figure 4.2: Flowchart for training a model

4.3 Flowchart For Testing

The test.py file is created for Predicting High resolution data from its corresponding low resolution data by following the Flowchart shown in Figure 4.3

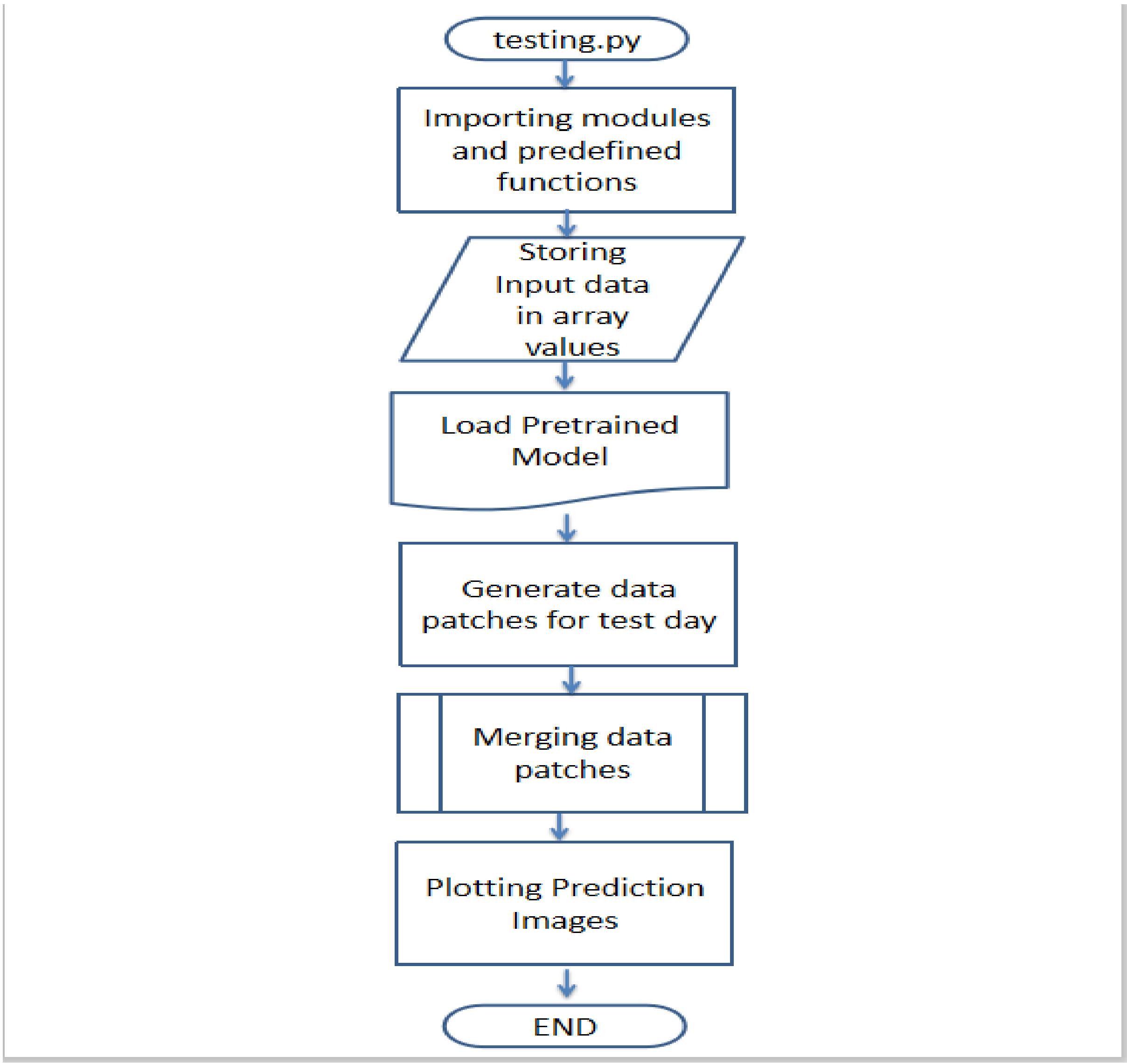


Figure 4.3: Flowchart for Testing a model

Chapter 5

Design of System

5.1 Sequence Diagram

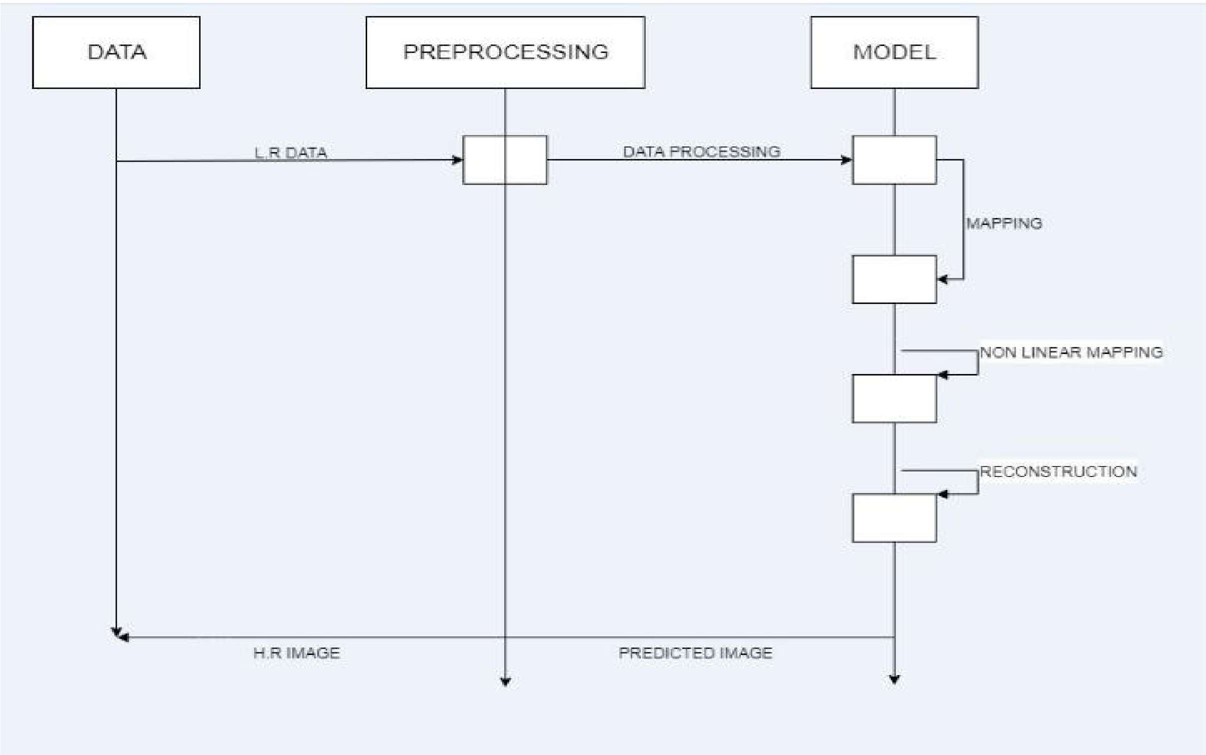


Figure 5.1: Sequence Diagram

The above diagram shows the sequence of order processes. The three Lifelines are shown in the sequence diagram. Messages sent by each lifeline are synchronous messages, as each process requires a response from the previous message. A total of seven steps are required for the corresponding Low Resolution Image in the sequence diagram and the generated high resolution image.

Chapter 6

Result

After training the model, it was able to predict high resolution 0.25-degree data from low resolution input in 1-degree format. The model is therefore able to increase the resolution of the input image by 4 times. The Figure 6.1 is an input image to the model (low resolution data) , second image is Actual high resolution data (Ground truth). Provided that the model is trained over a decade of data on high epochs can increase the accuracy of model.

Statistical validation includes the distribution of correlations and the MSE plot for comparison between different approaches.

6.1 Network Architecture

Both the SRCNN and DeepSD models consist of three Convolutional layers. Both have the same architecture but the difference is in the input-shape as deepsd includes one more parameter along with the variable. Detailed architecture as follows:

- First Convolutional layer has 64 Filters each having a kernal size of (9,9)
- Second Convolutional layer has 32 Filters each having a kernal size of (1,1)
- Third Convolutional layer has 1 Filters each having a kernal size of (5,5)
- Activation function PReLU is used in all the three layers

6.2 Model Parameters

Parameters used in model:

- Activation function = PRELU
- Kernel Initialisers = GLOROT Normal, Random Normal, Truncated normal
- Optimizer = ADAM
- Loss function = Mean Squared Error (MSE)
- Epoch = 1,500
- Batch size = 200
- Learning rate = 10^{-4}

6.3 Validation Data

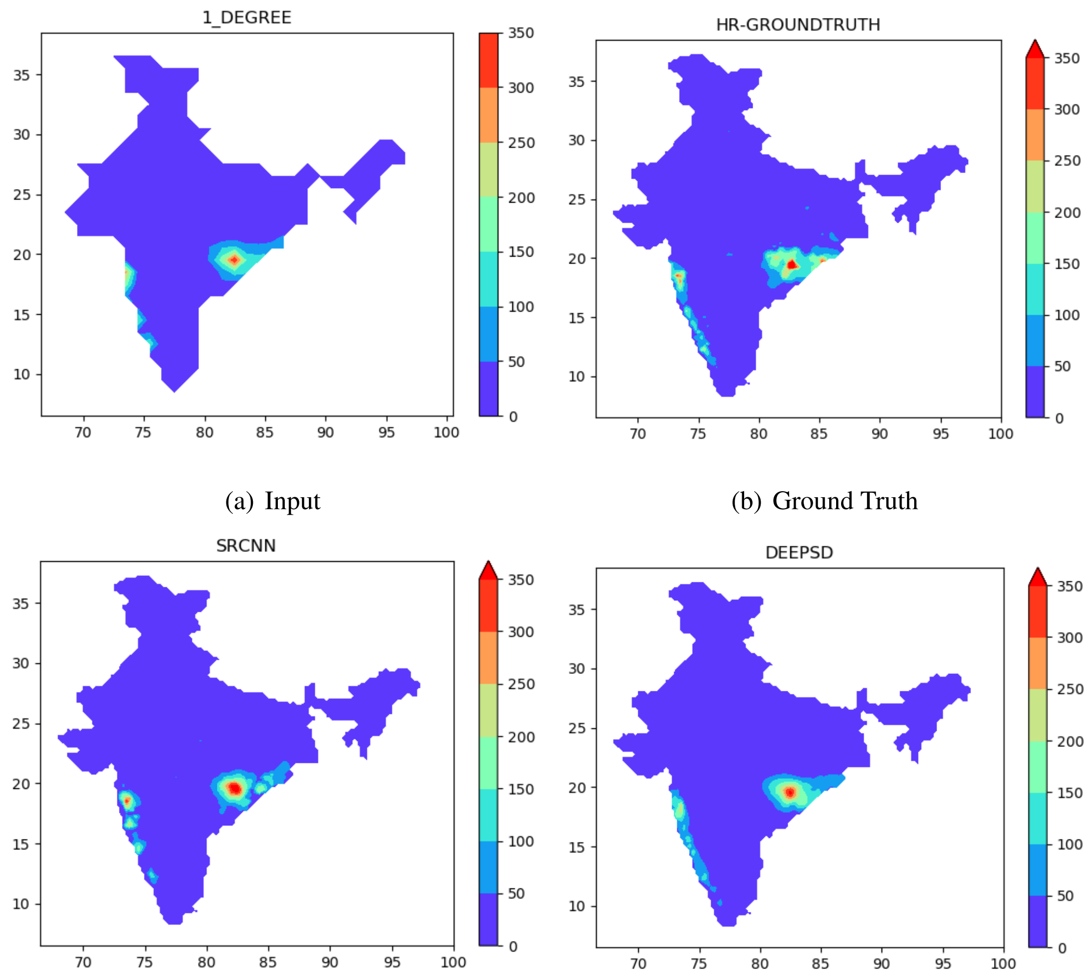
Model is trained on 30 Years (1975-2004) of data over 1,500 epochs and validated on separate data. Validation data details as follows:

- The validation for the above models has been carried out for monsoon data i.e. 151 days in a year (Jun-Sep)
- 5 years (2005-2009)
- Total no. of days = 605 days

6.4 Comparison of Results

After training the model, the model was tested for validation data. SRCNN and DeepSD have been able to capture the pattern from input data. Along with the topography input deepsd was capable of handling extreme event precipitation points. 1-Grade input (Fig. 6.1 a) is fed to the models to predict the corresponding 0.25 degree output using SRCNN and DeepSD methods.The output of the models is later compared with the corresponding Ground-Truth (Fig. 6.1 b) and also statistically validated.

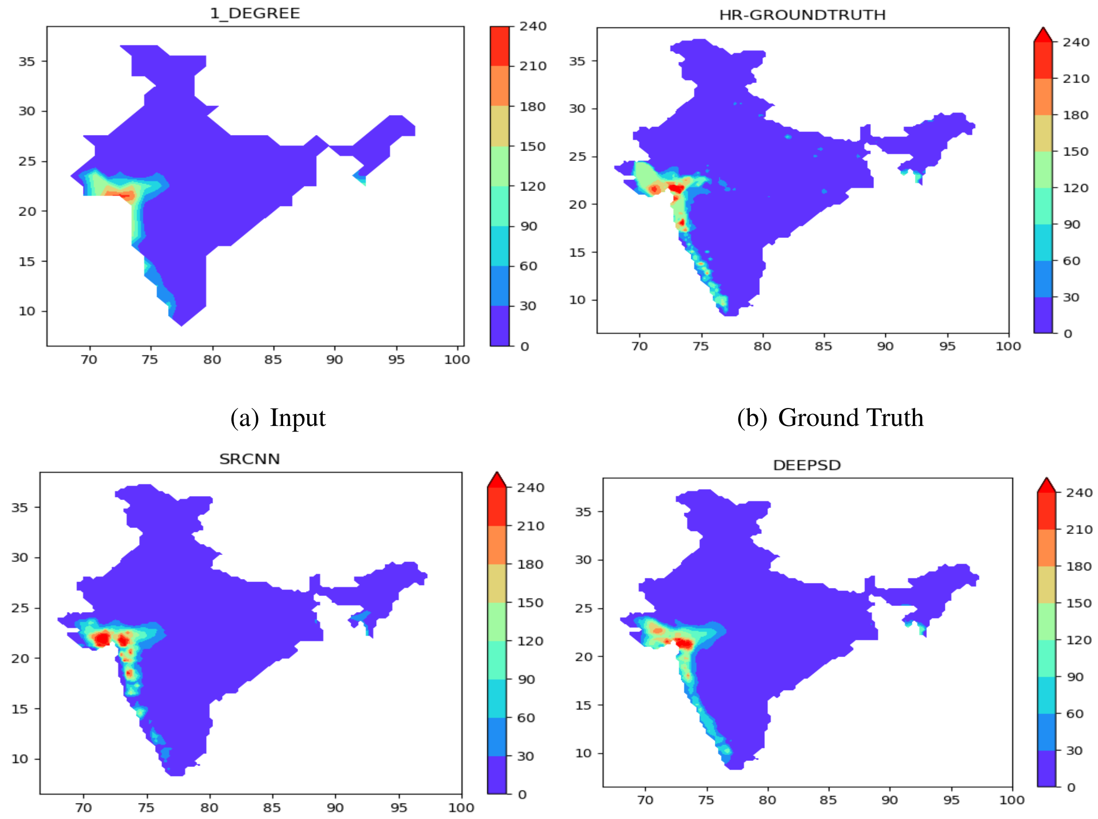
Figure 6.1 and 6.2 are the comparisons between input, ground-truth and predicted images using a trained model. Predicton, using SRCNN (fig 6.1 c) and DeepSD (fig 6.1 d) , clearly shows that they are capable of predicting extreme event precipitation as well as dealing exceptionally well with ill-posed problems.



(a) Input (b) Ground Truth

(c) SRCNN (d) DeepSD

Figure 6.1: Result Comparison



(a) Input (b) Ground Truth

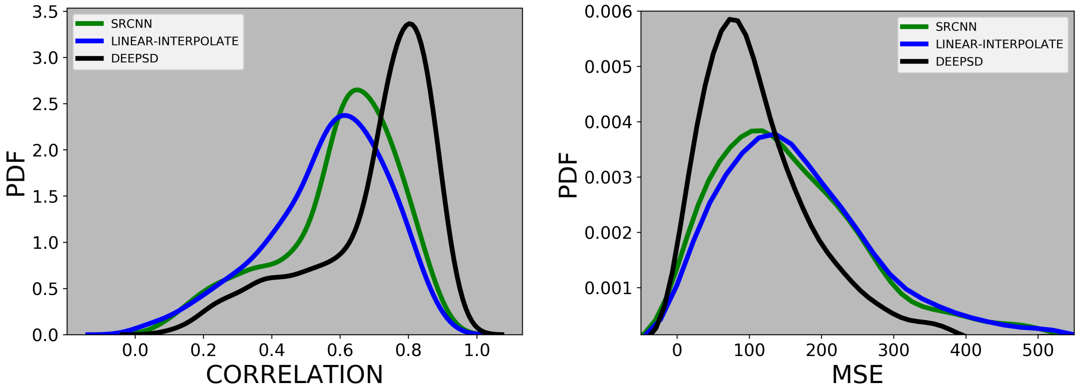
(c) SRCNN (d) DeepSD

Figure 6.2: Result Comparison Contd.

6.5 Statistical Validation

Statistic analysis is a way to understand the relationship of the variables.Visualization can be a key component of this method, as the human visual system can see trends and patterns that indicate a relationship if the data is correctly visualized.

The level of association shall be calculated by the coefficient of correlation referred to as the Pearson correlation coefficient (r) after its originator and is a linear association measure. The coefficient of correlation is measured on a scale from + 1 to-1. If one variable increases with the other, the correlation will be positive; if it decreases with the other, it will be negative. Statistical plots are univariate distribution of oberservations. Both MSE and Correlation plots consist of Gaussian distribution values of the corresponding x-axis values on the y-axis. Any dataset can be plotted as a PDF and that PDF corresponds to some distribution (in our case Gaussian distribution). In the case of the correlation graph, the value of the correlation will be given by projecting the peak point of the curve on x-axis. The higher the value of the correlation, the better the relationship between variables (methods and Ground-truths in our case). Similarly, an error value is provided by projecting the peak point of the MSE curve on x-axis. Thus, the variable with a low MSE value has a better relationship to the associated variable.

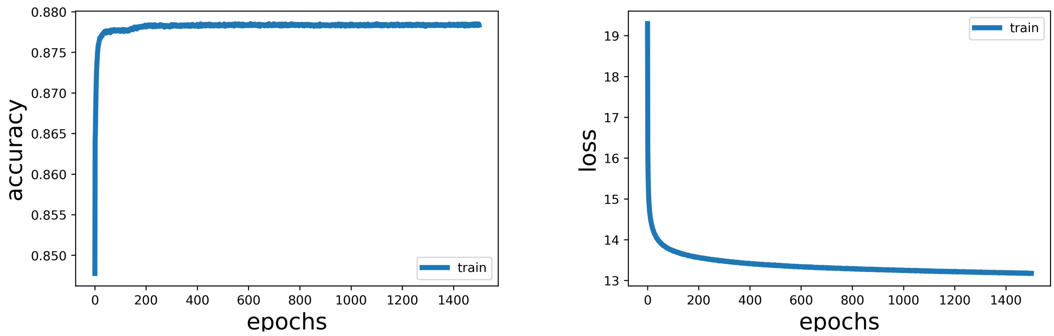


(a) Correlation

(b) MSE

Figure 6.3: Statistical PDF Plots

Figure 6.3 shows that DeepSD has a high correlation with ground truth when compared to SRCNN and linear interpolation. Likewise, SRCNN has more correlation than a linear interpolation technique.



(a) Model Accuracy graph

(b) Model Loss graph

Figure 6.4: Model Plots

Model plots which includes accuracy-vs-epoch and loss-vs-epoch graphs provide an indication of useful things about the training of the model, such as:

- Convergence rate across epochs
- Whether the model has converged already
- Whether the mode might be over-learning of the training data

This gives us a brief description of the training cycle and how the network is taught.

Chapter 7

Conclusion

Special architecture known as Single image super resolution on Convolution Neural network (CNN) to generate high resolution data from its corresponding low resolution data has been applied on meteorological data. SRCNN method, learns a mapping between low and high-resolution data with some pre/post-processing beyond the optimization. Multi-channel input, DeepSD performed exceptionally well to generate high resolution Meteorological data projections compared to traditional methods. SRCNN's three-layer convolution neural network model is applied to a low-resolution image that enhances the pixel-wise arrangement of a low-resolution image resulting in a high-resolution image that can be visualized later. An advantage of SRCNN is that a single trained model is able to downscale spatial heterogeneous regions.[2]

0.25 degree data is high-resolution data that is not readily available. However, low resolution data can be downscaled to 0.25 degree using the above methods. With a trained model, Gridded IMD data can be generated by downscaling 0.25 degree input to the desired format with some extra pre / post processing. Ability to further downscale High-resolution projections enables the extraction of regional-level climate patterns.

Besides, the proposed framework may be extended to other low-level vision issues, such as picture deblurring or simultaneous SR+denoising, with its advantages of simplicity and robustness.[1]

Chapter 8

Future Work

Potential research will strengthen many DeepSD aspects. For example, more climate trends are captured by the addition of more variables such as temperature, wind, humidity etc. It is also possible to explore multiple climate variables at the same time and similar spatial patterns in high-resolution datasets, such as high temperatures and increased precipitation.More specifically, DeepSD is struggling to achieve confidence regarding its downscaled predictions, which are essential to climate change adaptation. Recent developments in the principle of Bayesian Deep Learning may help measure uncertainty. Although some drawbacks remains, DeepSD is a scalable architecture that offers a modern statistical downscaling paradigm with strong predictive capabilities.

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Acknowledgement

I take this opportunity to express our profound gratitude and deep regards to my guide **Dr. Amit Barve** for his exemplary guidance, monitoring and constant encouragement throughout the completion of this report. I am truly grateful to his efforts to improve my understanding towards various concepts and technical skills required in our project. The blessing, help and guidance given by him time to time shall carry us a long way in the journey of life on which we are about to embark.

I take this privilege to express my sincere thanks to **Dr. Mukesh D. Patil, Principal, RAIT** for providing that much necessary facilities. I am also thankful to **Dr. Leena Ragha**,Head of Department of Computer Engineering, Project Co-ordinator **Mrs. Smita Bharne** and Project Co-ordinator **Mrs. Bhavana Alte**, Department of Computer Engineering, RAIT, Nerul,Navi Mumbai for their generous support.

I am also grateful to **Indian Institute of Tropical Meteorology(IITM), Pune** who gave me opportunity to perceive internship at IITM under Aritifical Intelligence/Machine Learning Domain and provide us necessary facilities. I am thankful to **Dr. Bipin Kumar** , **Dr. Rajib Chattopadhyay** and **Mr. Manmeet Singh** for the encouragement and support that they have extended. Their continuous guidance and direction for the project made this possible.

Last but not the least I would also like to thank all those who have directly or indirectly helped me in completion of this thesis.

Mr. Niraj Chaudhari