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Weather Forecasting Techniques using Artificial Neural Networks

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ABSTRACT
Weather forecasting has become an important field of research in the last few decades. In most of the cases the researcher had attempted to establish a linear relationship between the input weather data and the corresponding target data. But with the discovery of nonlinearity in the nature of weather data, the focus has shifted towards the nonlinear prediction of the weather data. Theadventofnewsatelliteimagingtechnologieshasmadesatellite images more accessible. These images can be utilized for weather predictions. This work proposes a simple approach for weather prediction that relies on satellite images and weather data as inputs. The method is divided into two parts. The first part involves the use of image processing techniques such as image segmentationonthesatelliteimagestoextractthecloudcover.On basis of the cloud cover obtained, percentage cloud cover is calculated and this calculated percentage value is stored, which is later used in the second stage of the approach. The second part involves the use of the cloud cover percentage along with other inputs such as temperature, humidity and wind speed to train an artificial neural network.
Keywords-Satellite Images, Image Processing, Artificial Neural Networks

I. INTRODUCTION

The interpretation of satellite weather imagery has generally required the experience of a well-trained meteorologist. However, it is notal ways possible, or feasible to have an expert meteorologist on hand when such interpretation is desired. Therefore, the availability of an automated interpretation system would be quite desirable. Also, to take advantage of this available data in a reasonable and useful time increment, the system must be efficient and have low implementation cost. There are 3 main types of satellite images available - Visible,

Infrared and Water Vapor. Visible images are obtained only during the day. They are used to determine the thickness of the clouds. Infrared images are obtained using special infrared sensors. The major advantage of this type is that it can be obtainedevenduringnight.Itcanbeusedtomeasure temperature of cloud top. Water Vapor images indicate the moisture content or humidity. The brighter areas tend to have high chances of rainfall.

Inrecentyearstheexponentialincreaseinprocessingpower has revived machine learning algorithms like artificial neural networks, linear and logistic regression. This has resulted in wide range development of machine learning algorithms for nearlyevery application, from handwriting recognition to solve crimes or predicting the stock market. Weather prediction using machine learning techniques is a field where much researchh as not been done. Predicting the weather is one of the most important and challenging aspects of remote sensing due to a large number of factors affectingit.

There has been significant progress in the area of remote sensing of satellite images using image processing methods. One of the strategies used for image retrieval and feature extraction is using fuzzy SOM strategy for satellite image retrieval and information mining projected by yo-pinghung,t sun-weiand li- jenkao [1]. They proposed a model for efficient satellite image retrieval and knowledge discovery. Ithastwomajorparts.First, it uses a computation algorithm for off-line satellite image feature extraction, image data representation and image retrieval.Aself-organization feature is used to create a two-layer satellite image concept hierarchy. The events are stored in one layer and the corresponding feature vectors are categorized in the other layer. Another strategy proposed by Craig M. Witten brinket. al is Feature extraction of clouds from GOES satellite data for integrated model measurement visualization [2]. The paper suggests a de-correlating transformation to the spectral images using Karhunen-Loeve Transformation (KLT) (moreproperly known as the Hoteling transform).TheKLThas been widely used in remote sensing for multispectral imagery, and is also known as principal component analysis. The principal components are obtained, and the firstn are selected. The choice ofn is a trade-off between low analysis complexity and accurate representation. The three main components are then

mapped into a3-Dhistogram. One of the more recent strategies is the use of ICA/Fast ICA Algorithm proposed by Du Huadong and Wang Yongqi is Studies on Cloud Detection of Atmospheric Remote Sensing Image using ICA Algorithm. In this strategy the 3 types of images (AVHRR) are used as input in the algorithm [3].The un-mixing matrix obtained from it can be used to segment clouds from the image.To show the different object in the separated
component more clearly, the normalization is done to the separated image. Apaperby Chiang Weietal suggests a multi- spectral spatial convolution approach for real-time rainfall forecasting using geostationary weathers atellite images[4].The approach incorporates cloud-top temperatures of three infrared channels in as patial convolution context.Thekernel function of the multispectral spatial convolution equation is solved by the least squaresmethod.

Initial studies in this area were donein 1998 inapapertitled “Localized Precipitation Forecasts from a Numerical Weather Prediction Model Using Artificial Neural Networks” byRobert
J.Kuligowski and AnaP. Barros [5].They proposed use of basic combination of back propagation neural network using a sigmoid function to predict data. Although most approaches in this area are restricted to the use of feed forward neural network. There have also been a few applications of different types of neural networks such as that by M.W Gardner and S.R Dorling in their paper titled “Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences” [6]. Here the authors present a general introduction and discussion of recent applications of the multilayer perceptron in the atmospheric sciences especially weather prediction.

II. PROPOSEDAPPROACH

The proposed approach of solving the problem consists of two main phases, the initial phase is the image processing phase where image segmentation is used to segment the satellite image of the region of interest (the region whose weather has to be predicted). After segmenting the image cloud cover over the required region is extracted in the form of apercent age value.

The next phase is the machine learning phase where weather data (humidity, temperature, etc.) is combined with the cloud cover obtained from the satellite image.This combined table of different parametersis then fed into anartificial neural network for training the model.

III. SATELLITE IMAGEPROCESSING

The section involves a list of steps. The first step is to perform image segmentation, in which the cloud features of interest are extracted from the original satellite image. The followings tepsthen involve feature analysisand interpretation. Here we wish to extract cloud cover from the images.The steps for cloud cover extraction are Image Segmentation, Region Separation using image cropping and Percentage cloud cover extraction.

A. Image Segmentation

For this part a simple algorithm is required which must achieve two goals. The first of which is to provide satisfactory image segmentation. These condgoalis to provide an algorithm which is simple to implement and has relatively fast execution.
Adaptive Average brightness thresh-holding (AABT) looks promising in addressing these two goals. This method is based on four observations [7]:

1. Amplitude thresh-holding is simple to implement and provides quick processing.
2. When correct threshold level(s) are chosen amplitude thresh-holding is highly effective.
3. Clouds are usually the brightest objects in a weather satellite image.

When processing a cloud satellite image, AABT follows a series of steps. First, the image is divided into approximately equal sized quadrants. Second, for each quadrant an average brightness level is calculated. Next, using an average cut-off functiona suitable cut-off thres hold is determined for each of the quadrants and applied to each region separately. Finally, the complete image is produced by recombining the sub-regions[7].
For the third step of this algorithm, the average cut-off function is given by:

$$\text{Cutoff}=\text{Avg.Brig}h\text{tness}+\mathbf{f}*(\ln(\text{GMAX})-\ln(\text{Avg.Brig}h\text{tness})) \quad (1)$$

Where:
ln() denotes the natural logarithm
G-MAX is the number of greyscale values in this case, G-
MAX = 256
f is a multiplicative coefficient, determined empirically, in this case, f = 22.5

B. Region Seperation

This technique involves cropping out the region for which the prediction is to bed one. This way a better view of the region is obtained. By observing the surrounding regions in the image weather conditions can be noted. Also processing of smaller images is faster and easier than large images. Although problem faced is that the resolution of image decreases as compared to the originalimage.

C. Cloud Cover Extraction and Percentage Calculation

The main aim of image processing is to obtain the cloud cover. The amount of cloud present in the region is determined by the cloud cover percentage. It serves as an important parameter for prediction of weather.
It is calculated by using this formula:

$$CloudCover(\%) = \frac{No.ofnonzeropiseSc}{TotaSno.ofpiseSc} * 100 \qquad (2)$$

Here pixel represents the values of the image matrix.
From this, weget the values of cloud cover.These values are used as input parameters for training samples through an artificial neural network.

IV. PREDICTION USINGANN

Artificial neural networks (ANN) form the basis for a number of computational models based on the mammali an brain [8]. Instead of depending on linear correlative relationships among a particular dataset, ANN is a form of machine learning in which the system learns to predictan output variable based on an input series. Data is processed by feeding it to a number of inter connected neurons which form synaptic connections.These connections follow a path from the input nodes through a hidden layer before ending on the output neurons. Each input and hiddenneur on consist of statistical weights which are capable of adaptation, the exact parameters which are modified by an algorithm over the course of network training procedures. The weights form the synaptic connections between neurons which are activated during network creation. This form of computing has the ability to operate in a parallel format, similar to the humannerv ous system. Because neural networks donot depend on linear dependencies for learning, ANNs are capable of nonlinear modeling and therefore, provide an alternative approach to a number of the oretical and real-worldproblems.
The following sub-sections explain the two types of neural networksusedi.e.Non-Linear Auto regressive(NAR) and Non- Linear Autoregressive Exogenous model(NARX).

A. Non-Linear Autoregressive Neural Network Model

This particular form of ANN is used in time series modeling in order to predict an outcome variable [y(t)] based on d past values of the outcome variable.The fit of predicted out putvalues can be compared to the original target values using simple correlationco efficients, while an errortermisalso employed in order to further gauge predictive accuracy, usually presentedas some form of mean or summed squared error term (target-output). taken at a duration of every one hour of each day for the year 2015.
The methodology implemented on a sample satellite image has been shown below:

A. ImageSegmentation
It is the first step of the method. The AABT algorithm is applied on the image. The result is as shown:
The methodology implemented on a sample satellite image has been shown below:

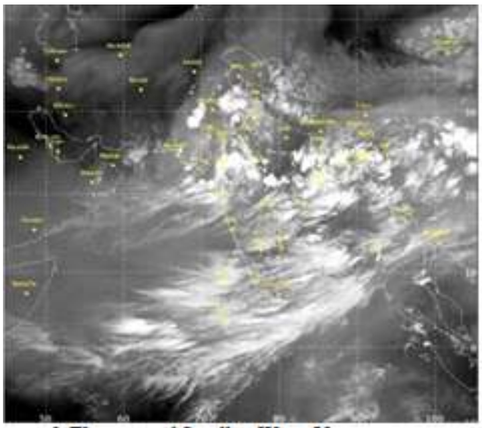

Figure 1. The original Satellite Water Vapour image.

$$y(t)=f(y(t-1),\ldots,y(t-d)) \quad (3)$$

The other neural network model used is the Non-Autoregressive Neural Network model with exogenous input (NARX).

B. Non-Linear Autoregressive ExogenousModel

This particular form of ANN isused in time series modelling in order to predict an outcome variable [y(t)] based on 'd' past values of the outcome variable and current as well as 'd' past values of an external source of influence [x(t)][9].Theaccuracy of the predicted output values can be compared with the original target values using correlation coefficients, while an error term is also used in order to improve gauge predictive accuracy, usually presented as some forms of mean/summed squared error term (target-output).

$$y(t)=f(x(t-1),\ldots,x(t-d),y(t-1),\ldots,y(t-d)) \quad (4)$$

V. IMPLEMENTATION PROCESS FOR SATELLITEIMAGE PROCESSING

To test the working and the performance of the method, it was applied on a dataset of images. This dataset was collected from the website of Indian Meteorological Department. The data set consisted of Waterv aporimages. The images used were

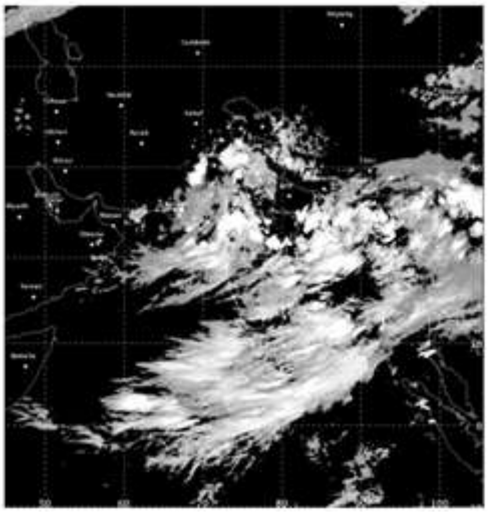

Figure 2. Segmented Image obtained after applying AABT algorithm

B. RegionSeperation

In this step, the region separated out is the Western region containing Mumbai. This is done because we want to test our approach for Mumbai region only. The region is selected and cropped out to get a new image.

$$NORN_{data} = \frac{(data - min\,(data))}{max\,(data) - min(data)} \qquad (5)$$

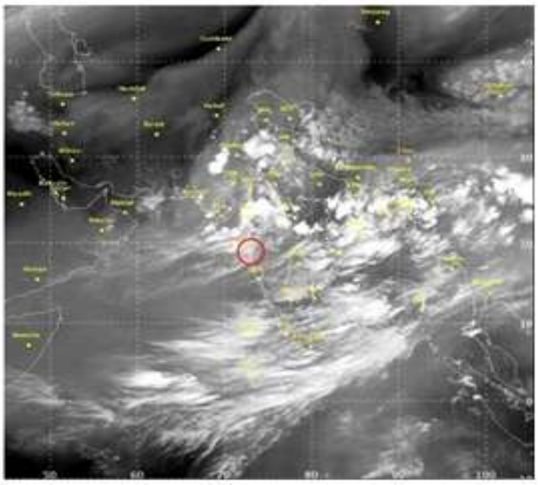

Figure 3.Region Selection for cropping.

Figure 4. Final Cropped Image

C. Cloud CoverExtraction

The cloud cover percentage is calculated based on the equations given. It is calculated from the cropped image. For the above image the cloud cover percentage obtained is 96%.

VI. IMPLEMENTATION PROCESS FOR PREDICTION

After Image Processing and Segmentation is complete,the cloud cover information is extracted and is combined with the weather data table to create a consolidated database which is then used for predicting different parameters.

A. Dataset integration andpreprocessing

The initial weather dataset consists of four weather parameters: Mean Temperature, Mean Humidity, Mean Wind Speed and Precipitation. The data derived from Image Processing and Segmentation consists of cloud cover over the chosen region. The values of cloud cover are divided into ten parts on the basis of 'greyness' of cloud cover, where a 'clear' sky is denoted by value '0' and an overcast sky is denoted by value '9'. The weather data is of Mumbai city from the period of June 2012 to June 2016 divided hourly. Therefore, there are 35, 040 values in thedataset.Thecolumnforhourlycloudcover values is added thedatasetAs the values in the dataset are of different ranges, the values are normalized before training them on the neural network. Normalization is done to scale down values of all columns of the dataset in the range of 0 to 1. The following is the normalized equation used.Where data is the data matrix or the dataset.

B. Training non-target parameters using NAR Neural Network

We have assumed that precipitation is a phenomenon that depends on the remaining five columns, but it is still necessary to predict the other parameters. As the other parameters tend to exhibitacy clicyearly pattern it is suitable to apply NAR model to predict the future value of data. Therefore, each column is initially independently trained except Mean Precipitation using the NAR Neural Network Model because it is the target. The training set is considered as the first 70% values of thedataset

This process is required as these predicted values for each of theremainingn on-target columns are required as initial input for predicting the target value using the NARX model.

C. Training and Prediction of mean precipitation using NARX Neural Network

NARX model is trained with x[(t)] as all the input columns(i.e. Mean Temperature, Mean Humidity, Mean Wind Speed,CloudCover)andy[(t)]as the

Mean Precipitation which is the target output. As explained above NARX model takes into accountanexternal series which may affect the target series i.e. y[(t)].
The final prediction is to obtain precipitation values. These values can be easily obtained by testing the above trained NARX neural network using the input values obtained from training the individual columns through the NAR neural network as explained in the previoussection.

D. Denormalization and Output
The data obtained from the output would still be in normalized form and it is necessary to de-normalize. The data is de-normalized using the following equation.

$$data=NinVal+ \quad nORN_{data}.*(NAXVAL-NINVAL) \quad (6)$$

Where minValis the minimum value in the normalized data matrix, maxVal is the maximum value in the normalized data matrix and normdata is the normalized data matrix. The de-normalization of the data is performed column-wise.

VII. EVALUATION ANDRESULTS

The model discussed above was created and implemented using the MATLAB's Artificial Neural Network Tool. Figure.shows a snapshot of the data used to train and test the model. Training, testing and cross validation data were split in the ratio of 70:15:15 so as to obtain the best results. Many visualization methods were used such as, Performance Graph Plot and Error Histogram Plot to determine the quality of results. Mean Square Error (MSE) was one of the main factors used for determining thequality of the obtained results and is depicted as a part of the performance graph plot. Other parameters for testing include 3 layers of hiddenneurons. Weights were assigned arbitrarily, i.e. according to the rules assigned to the toolbox.

T**ABLEI**.ASAMPLEFROMTHEDATASET

Mean Temperatu r e(C)	**Mean Humidity (%)**	**Mean Wind speed(km/h)**	**Cloud Cover**	**Mean Precipitatio n(mm)**
28	77	11	6	13.97
29	75	10	5	0.25
29	75	10	4	0
31	71	13	3	0
28	79	11	5	12.95
29	76	13	2	0

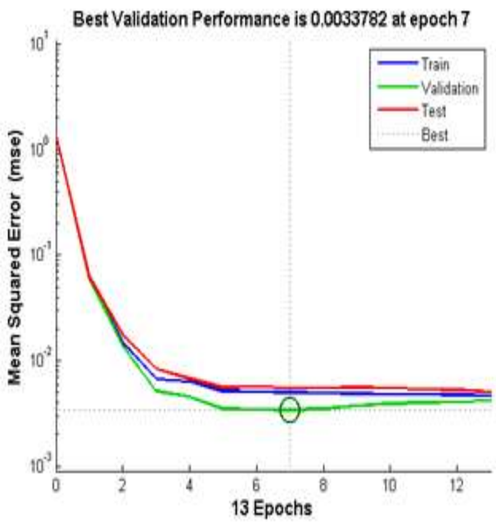

Figure 5. Performance Graph

The performance graph in Fig. 5 denotes the flow of the model during training of different aspects of the model i.e. training, validation and testing. The X-axis denotes mean squareerrorandY-axis denotes the epochs (aunitoftime).The green circle denotes the point having minimum MSE after convergence. The convergence of the graphis a clear indication that there is no over fitting. The best performance of the model was at epoch 7 where the MSE was 0.0033782. This is the best performance point of themodel.

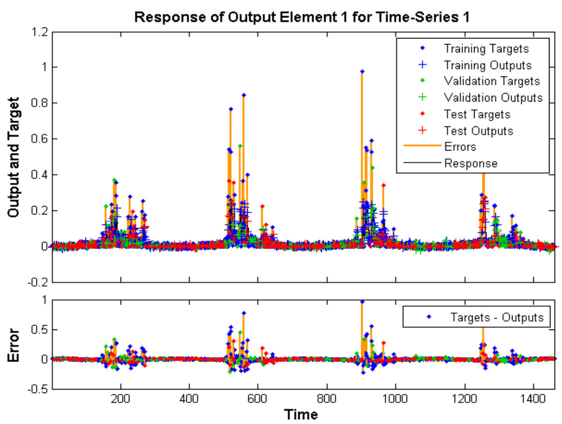

Figure 6. Time-Series Response Graph

The Time-Series Response Graph as shown below in Fig. 6 depicts the flow of error with respect to time. The lower graph indicateshowmuchthemodeldeviatesfromzeroerroro verthe period of training. The four major peaks in the graph indicate the arrival of the monsoon season in Mumbai for each year, during the four-yearperiod.

VIII. CONCLUSION

For an automated weather satellite image interpretation system, one of the key steps is image segmentation. In this process, significant cloud features are extracted from theimage and prepared for the next step in the process. AABT is designed to provide a fast and accurate method of image segmentation which is simple to implement as well. The segmentation results are provided quickly and with potentially enough accuracy to be integrated into a complete automated weather interpretation system or for cloud coverestimation.

Most Artificial Neural Network approaches preprocess the input and target data into a range -1 to +1 or 0 to 1 and then post-process it. However, we investigated on finding a model that can reduce this processing cost by working on raw data. Since we have 10 inputs, a 5 hidden-layer network with 10 or 16 neurons/ layer and a tan-sigmoid transfer function for hidden layers seemed to do generalize much better over 750 and 1460 samples as compared to a single hidden-layer network with the same number of neurons. We have already discussed the method to analyze and handle overfitting while aiming for accuracy in prediction. However the most important conclusion that our study resulted to was on the behavior of increased hidden layers on performance and generalization. It can be summarized as under: Finally, the prediction that we made for the maximum temperature can be extended to other weather factors like humidity, wind speed etc. using the same model and precautions discussed. Further measures to optimize the performance of such a weather forecasting model can be based on various macro and micro-environmental factors.

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