Daily Rainfall Prediction using Radar

Abdullah McDonald
Department of Computer Science, University of the Western Cape, South Africa
3708949@myuwc.ac.za

***Abstract*—Reliable daily rainfall predictions can play an important role in a) watershed management, b) disaster management, and c) helping people to plan their day. Numerous factors can have an effect on the patterns of rainfall and therefore it can be difficult to predict. Recent papers studied deep learning for rainfall prediction using various prediction models with an emphasis on short-term predictions (hourly), however, few have looked at daily rainfall prediction using deep learning. This paper discusses a deep learning model, ConvLSTM, for daily rainfall prediction using various sequence lengths of radar images and predicting 1, 2, 4, 7, and 12 days ahead. The aim of this paper is to investigate how well the ConvLSTM model fairs against a Multivariate Regressor and also to look at whether increasing the length of the sequences of images a model can learn from decreases the prediction error of the model. To establish the effectiveness of the ConvLSTM model, we compare it against the Multivariate Regressor and a Last Frame Regressor model. The results of our work show that the ConvLSTM model outperformed the Multivariate Regressor and Last Frame Regressor models when predicting 1 day ahead, however, when predicting 2, 4, 7, and 12 days ahead, the results of the ConvLSTM and Multivariate Regressor models are quite similar. When comparing sequence lengths, our results show that an increase in sequence length does not necessarily decrease the prediction error of a model.**

***Index Terms*—daily rainfall prediction, radar images, deep learning, machine learning.**

I. Introduction

Rainfall is a form of precipitation and is responsible for providing most of the freshwater for our planet [1]. A highly accurate and reliable rainfall prediction has an essential role in watershed management and water analysis in order to reduce the effect of natural disasters [2]. Predicting rainfall is also important since it can provide weather guidance for airports, manage floods, transportation, agriculture and manage the daily lives of people [3] [4].

Various factors can have an effect on the patterns of rainfall and therefore it becomes quite difficult to predict. Rainfall prediction requires a high spatiotemporal resolution and a high accuracy [3]. Radar echo maps represent electronic signals that have been reflected back to a radar antenna. These maps contain different colours that correspond to different intensities of precipitation. Radar echo rainfall images will be used in this study since they have the ability to provide a high spatiotemporal resolution for accurate prediction of rainfall.

The literature shows that there is plenty of research currently being done for applying deep learning to precipitation forecasting, specifically, rainfall. Deep learning has mainly become a talking point due to Convolutional Neural Networks ability to successfully classify images. Numerous research have thus been done to evaluate the use of convolutional neural networks on different types of images. In this paper, a deep learning technique will be used to predict daily rainfall.

This paper is divided as follows; Section II reviews the literature in terms of daily rainfall predictions, sequential and long-term rainfall rainfall predictions, and deep learning approaches to rainfall prediction; Section III looks at the dataset used, the preprocessing techniques used and also describes the proposed prediction model; Section V discusses the results of this paper; lastly, Section VI concludes the paper.

II. Literature Review

This literature review is divided into five sections. In the first section, we look at how previous papers went about their prediction of daily rainfall using daily rainfall satellite images and time-series data. Next, we have a section on deep learning techniques, LSTM and CNN, for the prediction of rainfall with a short time-frame. We then discuss how the length of the input sequences considered by researchers varies and also discuss long-term rainfall prediction. Following this, we look at research that used a pixel by pixel approach to predict on satellite images. Lastly, we explain how each of the previous sections contributes to the work of this paper.

Daily rainfall satellite images can provide valuable information for short-term as well as long-term events. Studies such as [7] looked at daily rainfall for short term rainfall predictions using satellite images. They considered two different approaches to the problem, a transfer learning approach and end-to-end training approach. The authors showed that the end-to-end training approach outperformed the transfer learning approach. By reviewing this study, we get a starting point for how to go about the prediction of daily rainfall using daily rainfall images. We also see that the authors of [7], modeled their problem as a classification task whereas this paper focuses on a regression problem.

Other papers such as, [5] and [8], also tackled the daily rainfall prediction problem with their research mainly focused towards rainfall derivatives. Rainfall derivatives define a contract between two or more entities where the value of the contract is determined by the financial asset, rainfall. The authors, Cramer et al., investigated the effectiveness of machine learning for the prediction of rainfall for weather derivatives, specifically rainfall derivatives and they investigated the difference between using daily rainfall versus accumulated rainfall for the prediction of rainfall derivatives. The dataset used consisted of 42 cities from the USA and Europe with different climatic conditions. The measured total amount of rainfall in the USA was higher than in Europe. The machine learning techniques used were Genetic Programming, Support Vector Regression (SVR), Radial Basis (RBF), M5, M5 Rules, M5 Model Trees and K-Nearest Neighbors. The testing metric used was the Coefficient of the variation of the RMSE [5]. Cramer et al. provide a good overview on the pitfalls of daily rainfall predictions, what to expect and also how machine learning algorithms fair in the task of daily rainfall prediction. When evaluating the machine learning algorithms, they also show that it is good to use baseline algorithms to demonstrate the effectiveness of one algorithm with respect to another.

There has been a consistent amount of research for the prediction of rainfall with deep learning techniques. This research either regarded the problem as a regression task or a classification one. Here we focus on the regression task where previous approaches predicted a full image as the output when given a sequence of images as input. We specifically focus on the ConvLSTM deep learning technique since it can locally store information of a past image when trying to predict a future image. In [9], Souto et al. investigated the use of a ConvLSTM model to predict rainfall. They wanted to predict up to 1 day ahead using a daily rainfall satellite dataset that contained 17 000 satellite images. As input, they took a sequence of 15 satellite images and output an image for the next day of the sequence. Their results showed that their ConvLSTM model outperformed two baseline models. Another paper, [3], proposed a ConvLSTM model with a layer called a star-shaped bridge. The dataset used consisted of radar echo images. They took a sequence of radar echo images as input and provided a 30 minute later radar echo image as output. The ConvLSTM model was trained on over 44 000 sequences of radar echo images. The authors compared their results to another baseline model and it showed that their model performed better. From these research articles, we can see the effectiveness of the ConvLSTM model and how it can be used for sequential image prediction problems.

Looking at research on rainfall prediction, nearly every paper makes use of different input sequence lengths. [3] makes use of an input sequence length of 20, [9] uses 20, and [15] uses 5. These papers do not mention any specific reason behind their choices. On the other hand, papers such as [16] and [17] uses input sequence lengths that correspond to their particular prediction time-frame. For example, doing hourly predictions using a rainfall image dataset that has a time difference of 6 minutes would require an input sequence length of 10 images. Moreover, when looking at the research that predicted rainfall on a daily basis, [5] and [8] was the only paper that produced long-term predictions, however, they used time-series data instead of radar or satellite images. These two aspects are focused on in this paper.

Furthermore, the work of [10] and [11] details a pixel by pixel approach for the prediction of future cloud formations in satellite images. Given a sequence of satellite images, this approach works by taking the value at a specific pixel location and its surrounding neighborhood pixels in every image in the sequence and using it to predict the future value of that pixel at a later time. They do this for every pixel in the image and the output of this method results in a future image in the sequence. This approach provides a convenient way of predicting future satellite images when having a small dataset and thus a variation of this approach will be used in this paper.

Motivated by the work above, we will compare a ConvLSTM model to a Multivariate Regressor for the task of daily rainfall prediction for different input sequence lengths (4, 8, and 12) and predict a particular number of days ahead using these sequences (1, 2, 4, 7, and 12). The daily rainfall dataset that will be used from the National Centers for Environmental Prediction (NCEP) and contains radar rainfall images. We will also consider different preprocessing techniques for the prediction models, with one being a variant of that showed in [10] and [11]. The primary aim of this work is to show the effectiveness of the ConvLSTM model and investigate whether longer sequences lengths can produce better results.

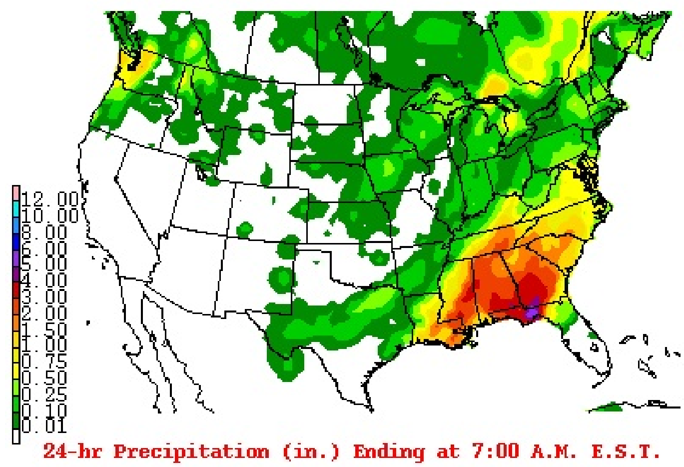

Fig. 1: Dataset sample image

III. Methodology

In this section we start by discussing dataset used for this paper, the preprocessing techniques that was carried out in a step-by-step manner, the ConvLSTM model, and lastly, we discuss the training-testing split for the dataset.

A. Dataset

The dataset used for this study was collected by the National Centers for Environmental Prediction (NCEP). It contains radar rainfall images that records the rainfall intensities over USA. These radar images were captured at 7 a.m., Eastern Standard Time, everyday from January 2012 to October 2019. This dataset consists of 2834 images with an image resolution of 400x320 pixels. The rainfall intensities recorded on the images are coded into 16 different categories as shown in Figure 1.

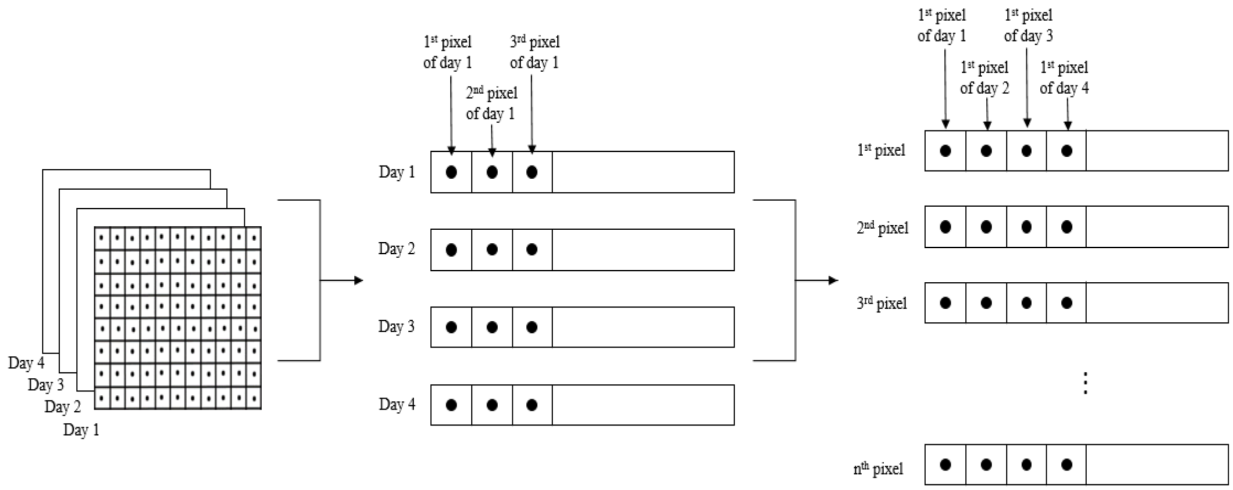

Fig. 2: Preprocessing Images using Sliding Window Technique

B. Preprocessing

The images of the dataset underwent some transformations in order to produce training and testing sets for the prediction models. These transformations are broken down into 3 steps:

1) Cropping, Grayscale Conversion & Resizing: The images in the dataset were cropped to remove static information. The color-bar along the side of the images as well as the words indicating the time of capture of the images were removed and this resulted in the images having a resolution of 357x244. After cropping the images, it is converted to grayscale and then resized to 100x100. The reason for resizing the images is to decrease the complexity of our model and also decrease the error of the predictive models [16].

2) Color-Bar Value Replacement: To allow for more accurate predictions, this step replaces the 16 color values from the grayscale conversion on the regions with the 16 rainfall intensity values depicted on the color-bar shown in Figure 1. Going from a value range of 0-255 to 0-12 allows our model to speed up the computations of our chosen optimization function.

3) Sliding Window Technique for Regions: From Figure 2 we see how the image arrays of the regions are formatted using a sliding window technique. For this step, we have separate processes for the ConvLSTM and the Multivariate Regressor models. With the ConvLSTM model, we only create a sliding window of images as shown on the left of Figure 2. However, for the Multivariate Regressor model, we flatten the pixels of each image and then produce the feature maps shown on the right of Figure 2, where the pixels of the images are ordered in a specific way.

For this study, we make use of all 8 years of data from the dataset to create training, validation, and testing sets for the sequence lengths of 4, 8, and 12. The years 2012-2017 was chosen as the training set, the year 2018 was chosen as the validation set, and finally, the year 2019 was chosen as the testing set. We create training and testing sets for sequence lengths of 4, 8, and 12 and then predict 1, 2, 4, 7, and 12 days ahead with each of the models using these training sets. We then evaluate the models on their respective testing sets.

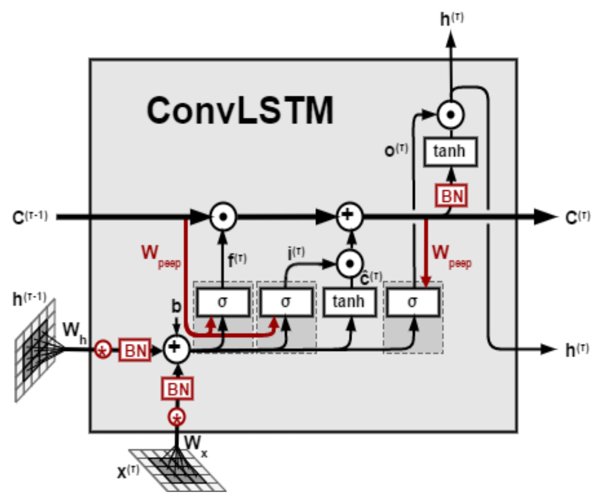

Fig. 3: ConvLSTM cell

C. ConvLSTM

The ConvLSTM model is a type of recurrent neural network (RNN) used in sequential problems. This model is similar to the LSTM model in that it makes use of gates to control the flow of information in the recurrent structure, however, unlike the LSTM model, it takes an image or a sequence of images as input. The ConvLSTM model combines the advantages of the CNN and LSTM models in that it can automatically extract important features from images, it can hold features over long time steps, and can overcome the problem of exploding and vanishing gradients. Figure 3 shows an example of an ConvLSTM cell. This cell contains a convolution operation which extracts features from the input sequence of images, a memory unit that keeps information over time, and gating units which regulate the flow of information in and out of the memory. The types of gating units found within a ConvLSTM cell are the input, output, and forget gates. The input gate controls how much new information is added to a cell state from the current input, the forget gate manages what information to discard from memory, and the output gate conditionally decides what to output from memory [12] [13].

Hyper-parameters are values used to control the learning/training process of a model and therefore can affect the efficiency of the model. To produce effective results, we need to find the optimum hyper-parameters of our ConvLSTM model and therefore we make use of the Bayesian Optimization method [14]. The hyper-parameters chosen to be optimized were:

- units: amount of units in a ConvLSTM cell
- kernel size: used to extract features from feature maps
- activation: type of activation function used
- recurrent activation: type of activation function used
- dropout and recurrent dropout: fraction of the units to drop for a ConvLSTM cell
- optimizer: updates the ConvLSTM model with respect to loss function

IV. Experimental Setup

For our work, 2 experiments were set out, the first one being to investigate which model would perform better on the dataset, and the second, whether an increase in the sequence length would result in a decrease of the prediction error. To ensure that we have a standard point of reference for each model and to further show their effectiveness, we make use of a Last Frame Regressor. The Last Frame Regressor merely takes as its predicted output, the last image in a sequence. The 2 experiments were conducted on a machine that ran Windows 10 and has an Intel i5 processor and 8GB RAM.

For both experiments, the Root Mean Squared Error (RMSE) metrics was used. The RMSE is a standardized way for measuring the error of a prediction model and it represents the norm of the distance between the predicted values and the ground truth values.

V. Results

This sections analyzes the results of the experiments. Tables I, II, and III shows the results obtained for each prediction model for sequence length 4, 8, and 12 when predicting 1, 2, 4, 7, and 12 days ahead. We first compare the prediction models against each other to see which model performed best and then discuss whether an increase in the sequence length decreases the prediction error of the models.

A. Comparison of Prediction Models

Table I shows the measured RMSE results for the various models for a sequence length of 4. From this table, we can see that for 1, 2, 4, 7, and 12 days ahead the ConvLSTM model performed better than the Last Frame Regressor and the Multivariate Regressor models. The Last Frame Regressor showed the worst performance. For 1 day ahead, we can see that the ConvLSTM model outperformed the Multivariate Regressor by 4.14% and the Last Frame Regressor by 25.38%. A similar performance difference between the ConvLSTM model and the Last Frame Regressor was obtained for 2, 4, 7, and 12 days ahead, however, we see that the ConvLSTM model and the Multivariate Regressor performing similar with the ConvLSTM model performing slightly better. This slight performance difference between the ConvLSTM model and the Multivariate Regressor may be due to the small size of the training set as a ConvLSTM model usually takes large amounts of data to find effective patterns in the data [16] [17].Figure 4-8 shows predicted images for 1, 2, 4, 7, 12 days ahead for a sequence length of 4 to further supplement the results discussed above.

From Table II and III we see similar results as above for the sequence length of 8 and 12. For a sequence length of 8 and predicting 1 day ahead, the ConvLSTM model outperformed the Last Frame and Multivariate Regressor models by 24.17% and 2.31% respectively. With a sequence length of 12, the ConvLSTM model had a performance difference of 24.45% with the Last Frame Regressor model and 2.4% with the Multivariate Regressor model.

TABLE I: Table showing the RMSE for a sequence length of 4 for the varioius regressors

	1 Day Ahead	2 Days Ahead	4 Days Ahead	7 Days Ahead	12 Days Ahead
Last Frame	0.19595	0.21136	0.21118	0.21171	0.21498
Multivariate Regressor	0.15253	0.15560	0.15594	0.15683	0.15807
ConvLSTM	0.14621	0.15376	0.15371	0.15382	0.15448

TABLE II: Table showing the RMSE for a sequence length of 8 for the varioius regressors

	1 Day Ahead	2 Days Ahead	4 Days Ahead	7 Days Ahead	12 Days Ahead
Last Frame	0.19627	0.21173	0.21174	0.21260	0.21503
Multivariate Regressor	0.15236	0.15534	0.15591	0.15668	0.15717
ConvLSTM	0.14884	0.15292	0.15454	0.15424	0.15484

TABLE III: Table showing the RMSE for a sequence length of 12 for the varioius regressors

	1 Day Ahead	2 Days Ahead	4 Days Ahead	7 Days Ahead	12 Days Ahead
Last Frame	0.19722	0.21272	0.21277	0.21304	0.21552
Multivariate Regressor	0.15266	0.15545	0.15618	0.15646	0.15655
ConvLSTM	0.14899	0.15372	0.15457	0.15465	0.15436

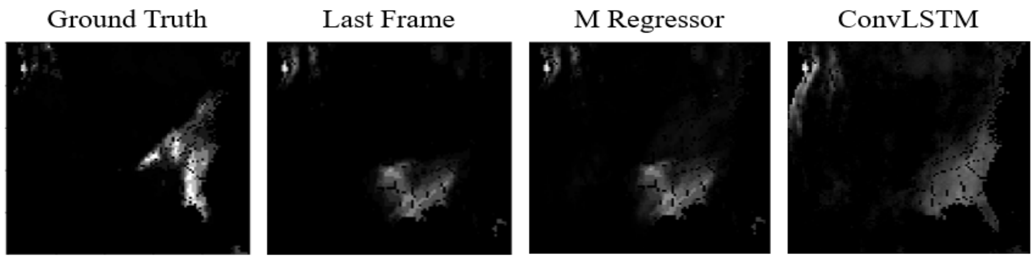

Fig. 4: 1 Day ahead prediction with sequence length of 4

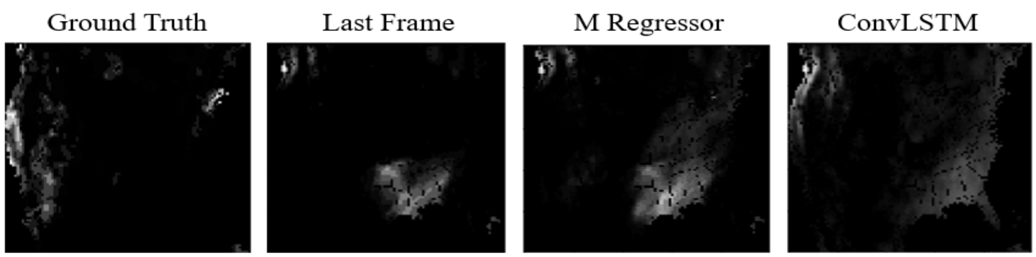

Fig. 5: 2 Days ahead prediction with sequence length of 4

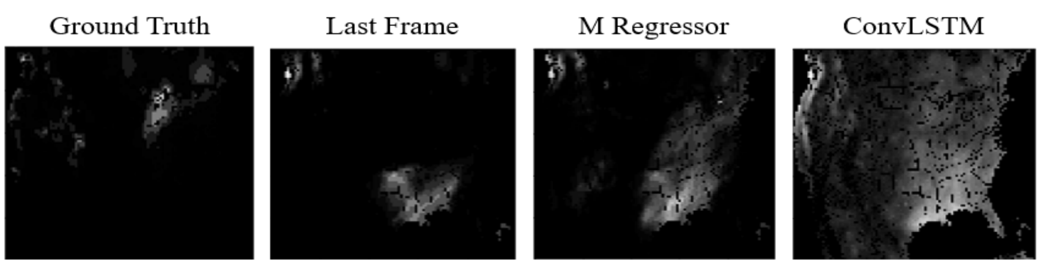

Fig. 6: 4 Days ahead prediction with sequence length of 4

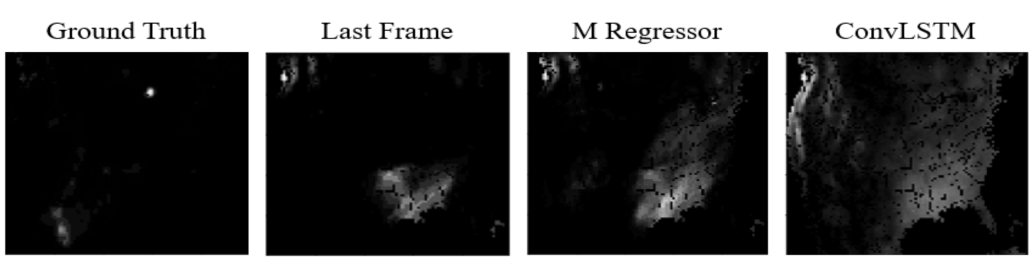

Fig. 7: 7 Days ahead prediction with sequence length of 4

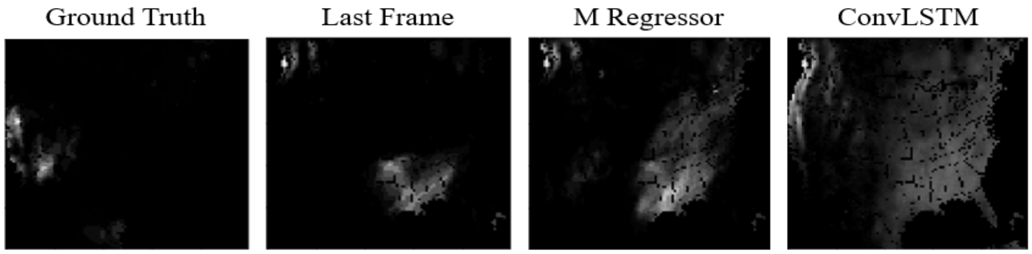

Fig. 8: 12 Days ahead prediction with sequence length of 4

B. Sequence Length Comparison

As mentioned earlier, the aim of this experiment is to investigate whether longer sequence lengths provide better predictions. From Tables I, II, and III we see that as the sequence length increases, this doesn't necessarily produce a lower RMSE value for any of the models. Let's take the ConvLSTM model as an example, for 1 day ahead, the RMSE value decreases as the sequence length increases. However, when we look at 2 days ahead for the various sequence lengths, we now see that the RMSE decreases from a sequence length of 4 to 8 but then increase from 8 to 12. Using this evaluation we can state that an increase in the sequence length does not necessarily produce a better prediction (lower RMSE). The results produced can be a cause of many effects such as a seasonal change in a sequence, not having enough training data for a longer sequence to effectively produce a desired result, and even the butterfly effect, which is the notion that small or minuscule changes in a certain property (pixel intensities in rainfall images for example) can have massive consequences in a particular outcome (predicting future rainfall images) [18].

VI. CONCLUSION

In this paper, we discussed the use of a deep learning model, ConvLSTM, for daily rainfall prediction when given different sequence lengths and predicting a certain number of days ahead. We carried out 2 experiments, investigating what prediction model performed best on the given dataset and whether an increase in sequence length decreases the prediction error. To show the effectiveness of our approach, we compared the ConvLSTM model against Multivariate Regressor and Last Frame Regressor models. The results of our paper showed that the ConvLSTM model outperformed the Multivariate Regressor and Last Frame Regressor models when predicting 1 day ahead for each of the chosen sequence lengths. The results obtained for the 2, 4, 7, and 12 days ahead prediction were quite similar between the ConvLSTM model and the Multivariate Regressor model. Due to the similar results obtained between the ConvLSTM and Multivariate Regressor models, we can see that complex deep learning models does not largely outperform machine learning and therefore we should consider various machine learning models for daily rainfall prediction before going the deep learning route. When looking at the sequence length comparison results, we saw that we could not conclude that an increase in sequence length decreases the prediction error as the results were indeterminate. Future work on this paper could include using a larger dataset to further investigate the sequence length comparison experiment.

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