

Development of a Rainfall Prediction Model using Convolutional Neural Network Architecture

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Abstract

Activities such as farming, road construction, and travelling, largely depend on rainfall. The prediction of rainfall is crucial so one can plan movement, when to plant, and when to carry out construction work to prevent loss of lives and property. Therefore, this research aims to develop a model that can improve the accuracy of rainfall prediction. The goal of this research is to create a Convolutional Neural Network (CNN) that could predict rainfall. Unlike traditional models that take in weather features in a vector form for rainfall prediction, our model takes these features as a 2D array. This approach allows the CNN model to learn spatial features from the 2D feature array, improving its accuracy. The CNN layer is then followed by the fully connected layer, and finally the regression layer. We compared the proposed model against the traditional approach of using the Correlation Coefficient. The proposed model had a score of 0.6404 as against the traditional approach with a score of 0.622. The integration of the CNN layer improved its accuracy. This research, therefore, shows that transforming weather features into a 2D array has the potential to improve rainfall prediction.

Keywords: Deep learning, convolutional neural network, regression, rainfall prediction, and artificial intelligence.

1. Introduction

Rainfall is a critical meteorological factor that has a direct impact on a variety of fields, including agriculture, hydroelectric power, and water resource management. Hydroelectric generation is mostly dependent on rainfall in the catchment region all over the world (Salami, et al, 2021, Arfasa et. Al, 2024, Darko, 2024). Recharging depleted groundwater resources requires adequate rainfall. Rainfall is essential in shaping the vegetation and wildlife of natural ecosystems (Salami, et al, 2021). It is formed when saturated air is heated and rises either by conventional currents or frontal action. The current dynamics of climate change strongly suggest that one needs an intelligent system that could be used to predict rainfall to sustain lives (Animashaun et al, 2020). As a result, it's more important than ever to study changing rainfall patterns and develop accurate predictions (Ibebuchi and Abu, 2023). This also goes beyond preserving human lives by making food available, but also for the prevention of natural disasters which could be caused by heavy rain, which was not anticipated (Ibebuchi and Abu, 2023). Therefore, having a system that can predict rainfall intensity is critical for preserving lives, natural resources as well as water management.

Water management is also important not for drinking but for crop production. Rainfall prediction will guide as too much one needs to invest in its storage for irrigation, for the supply of clean water, and then how

much one needs to reserve for the dry season (Ayoola, 2022, Durodola, et. Al, 2014). This therefore shows that the ability to predict rainfall could potentially be harnessed for the collective good of a given community.

Exact and accurate rainfall forecasts can aid not only in the efficient and effective use of this natural resource but also in the administration of power generation projects and plans.

Developing a system that can assist in the prediction of rainfall is therefore crucial (Emetere et al, 2024). One of the major contributing factors to the lack of management of water reserves is incorrect or poor rainfall prediction. Rainfall forecasting that is exact and accurate can help with not only the effective and economical use but also in the generation of power (Emetere et al, 2024).

Artificial Intelligence (AI) provides an avenue to develop a system that reflects how humans behave Chavlis and Poirazi, 2021 Assunção et al, 2023, Fan et al (2023), Isiaka et. Al, (2024), Sai et al, (2024). Specifically, an artificial Neural Network (ANN) is a kind of AI that leverages neurons (Sai et al, 2024). Just like neurons in our brains. These neurons are adjusted, during training, so that at the end, they can make accurate or close to accurate predictions (Shaikh, L. and Sawlani, K., 2017). ANN can access input information and process it for useful output. Artificial intelligence (AI) techniques are currently being widely used by scholars as a remedy to the enumerated issues faced by empirical models for rainfall prediction. This is due to the AI's ability to solve very vast, difficult mathematical and real-life issues reliably. The strategies can adapt to the data set completely without the use of any modelling assumptions.

Researchers such as Yaseen et. Al (2018), Abbot and Marohasy (2012), Diez-sierra and Jesus (2020), and Moon et al (2019) have shown that a variety of AI methods, including adaptive neuro-fuzzy inference system, the support vector machine (SVM), have been implemented to predict the amount of rainfall in a different region of the world. They were able to anticipate the amount of rainfall by up to a larger proportion, and their methods for using AI models are generally adequate. However, it was noted that there were differences in the models' time scales and input variables.

Adigun and Ebiendele (2019) came up with an AI model for predicting rainfall in Lagos, they used a four-layer deep learning model to achieve this where the input to the model is a column vector. More recent research has also been carried out for complex terrain as seen in He et al (2023), and an LSTM approach is proposed by Wang et al (2021) with promising results. Precise rainfall prediction is not only a scientific endeavour but also an essential requirement for several industries, from agriculture to water resource management (Wu et al, 2023), (Mafi-Gholami et al, 2020).

This research borrows the idea of Sharma, et al (2019) and Zhu et al (2021). In their work, they transformed data points into a 2D array before model training. They showcased the potential of transforming data points into a 2D array. In addition, the research carried out by Haidar and Verma (2018) showed that a 1D convolutional model can improve prediction. However, in this research, we used a 2D approach to solve the problem of predicting rainfall.

2. Related Works

Authors have used the traditional approach to rainfall prediction. For example, research by Kala and Vaidyanathan (2018) and Adigun and Ebiendele (2019) show how this is done by converting features of rainfall into a vector – this means that the input features are turned into a column vector and sent into the deep learning model. This has been the traditional way of developing models that could potentially predict rainfall. In addition to this, authors have also used the time series approach which is similar to the approach

by Wani et al. (2024). In addition, the U-Net CNN model has also been used, as seen in Badrinath et al. (2023). One downside to the column vector approach to deep learning could be that the deep learning architecture may not learn the unique spatial characteristics of these input features (Haidar and Verma, 2018). This is the motivation behind this work – the ability to turn rain features into a 2D array such that the deep learning CNN layer could learn spatial features. The rain features considered are average temperature, wind speed, wind direction, humidity, and pressure. These features are presented as a column vector. Data presented in a column vector lacks spatial context. We therefore reshaped it from a column vector into a 2D array, as seen in Figure 1, before passing it into the developed model. This created the spatial context necessary to apply filters to the 2D array for feature extraction. This allows for the extraction of relevant spatial information via the filters. Additionally, transforming a column vector into a 2D array enables the convolutional layer to capture correlations between rainfall features, potentially producing a better model that can generalize more effectively and improve accuracy.

3. Methodology

The dataset was acquired from Weather (2022) which consists of 9431 data points. Each data point has five features. These features are average temperature in Celsius, wind speed in Kmph, Wind direction in degree, humidity, and pressure in MB. These features are necessary to predict the nature of rain. The proposed mode was trained on 9328 data points and then evaluated on 103 data points. The training process was carried out for 1000 epochs.

The proposed model has five layers, which makes it a deep neural network. Since the input is a 2D array, the first layer of the model takes in this array size, and then it is convolved with 16 filters of size 2 by 2. The output of this layer is fed into the second layer which has 4 neurons, and then to the third dense layer of two neurons. Finally, to the last layer of one neuron. In Equation. 1. T is the ground truth value, while PP is the model's prediction. The loss function, in Equation, 1, is used to estimate the model error, this error function is also referred to as the mean square error (E , in Equation 1), the Adam optimizer (Şen, S.Y. and Özkurt, N, 2020) was also used to minimize the error during the backward pass. The five features considered for this research are average temperature in Celsius, wind speed in Kmph, Wind direction in degree, humidity, and pressure in MB. This forms a column feature vector of size 1 by 5. However, to convert this into a 2D array form, we added a dummy feature of a constant value of 0.001. This then makes it a 1 by 6 feature. This vector is then broken into 2 vectors of size 2 by 3 – invariably converting it into a 2D array (Figure 1).

The 2D array then serves as the input to the proposed deep learning model. The first layer (consisting of 16 filters) extracts feature maps from the 2D array, these maps are then flattened and then passed to the next layer until it gets to the last layer. At the last layer, the mean square error function calculates the model error, using the specified optimizer (Adam), the weights of the model are adjusted to further minimize the error.

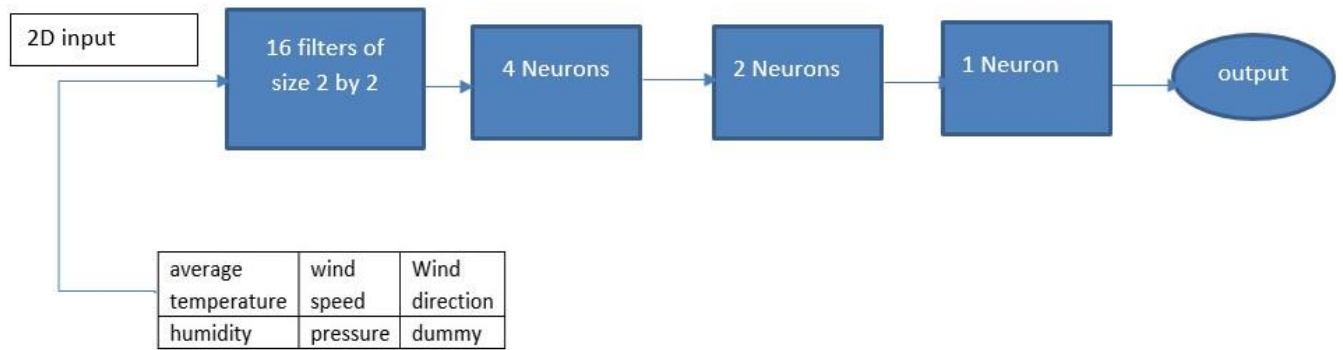


Figure 1. The proposed deep learning model uses a 2D array as input

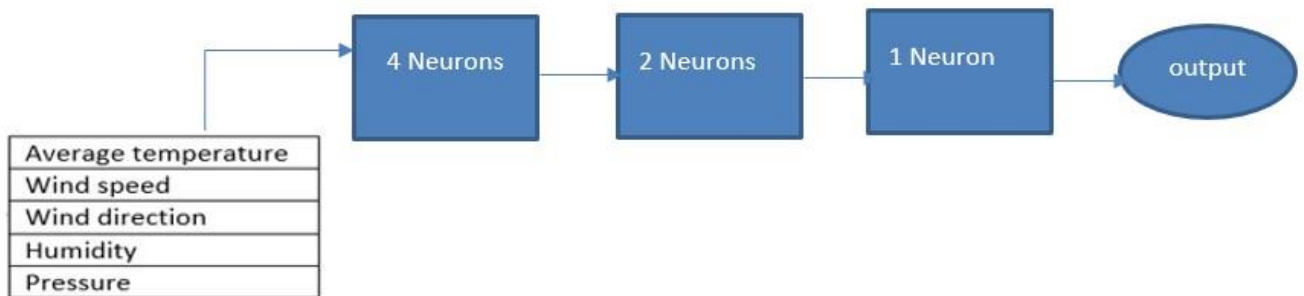


Figure 2: Traditional deep learning model (Adigun and Ebiendele, 2019) that takes in a column vector, as input

$$E = (T - PP)^2 \tag{1}$$

We also implemented the traditional model proposed in Adigun and Ebiendele (2019) as seen in Figure 2, here, the filters have been removed since the input is in a column vector. This was also trained on a similar dataset used in Figure 1.

4. Results and discussion

We evaluated the proposed model based on Pearson Correlation (R) as well as the cumulative error with 103 data points. For a reliable model, its R-value must be greater than 0.5. A value of 0.5 and above suggests that the model has a strong correlation with observed datasets. The proposed model that takes input as a 2D array has an R-value of 0.6404 while the traditional model takes in a

column vector has an R score of 0.622 (Table 1). Figures 3 and 4 show the correlation graphs respectively.

Table 1. Performance Evaluation

Model	R(Pearson Correlation)
Proposed model with 2D array as input	0.6406
Traditional deep learning approach	0.6222

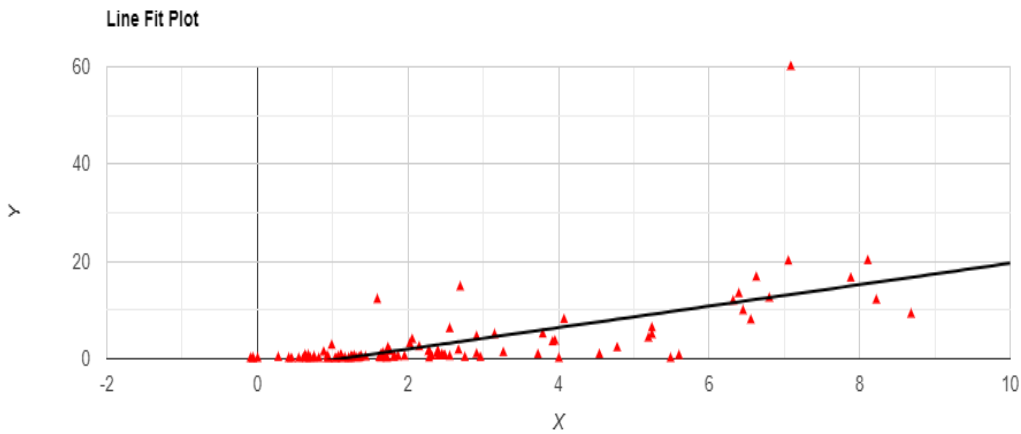


Figure 3: Pearson Correlation of the proposed model -X represents the input features, and Y is the level of rainfall in MM – generated by <https://www.statskingdom.com/correlation-calculator.html>

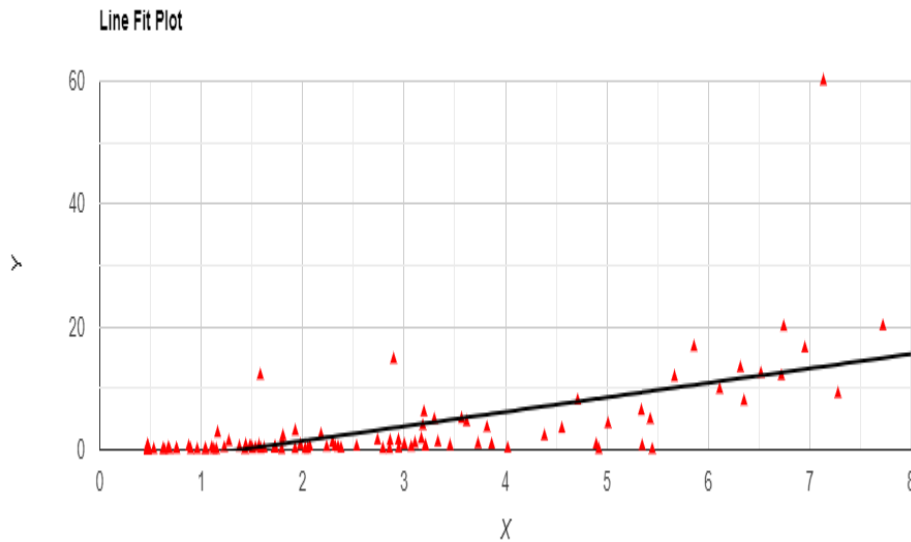


Figure 4: Pearson Correlation of the traditional model in Fig 2 -X represents the input features, and Y is the level of rainfall in MM – generated by <https://www.statskingdom.com/correlation-calculator.html>

$$CE = \sum_1^{103} (T - P) \tag{2}$$

We also used the CE in Eq. 2 (where T is the ground truth and P is the predicted) to estimate the cumulative errors in both models as seen in Table 2. As shown, the proposed model with a 2D array as input has less cumulative error as compared to that which takes in a column vector.

Table 2. The models' assessment utilizing the cumulative error (CE)

Model	CE
Proposed model with 2D array as input	245.315
Traditional deep learning approach	286.116

One factor that contributes to the performance of the proposed model is the fact that the conversion of the input feature into a 2D array enables the 16 filters to extract features from all the 5 input features together, this means these filters extract information based on the relationship that exist between them, before passing to other layers down the model, this is contrary to the model

(traditional) that takes input as a column vector into the model, where 2D spatial features are not exploited.

5. Conclusion

This paper dives into a comparative analysis between two deep learning models – one that takes in a column vector as input, and another that takes input features as a 2D array. It is observed that the model that takes in input features as a 2D array outperforms that which takes only a column feature vector. The reason is that passing a 2D array allows convolution filters to extract features within the context of each data point before sending them to the next layer. This singular act enriches the extracted features, keeping in mind the relationship that exists amongst these features.

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