A Hybrid TCN-BiLSTM Model for Enhanced Precipita.tion Nowcasting

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1. Abstract.

Precipitation nowcasting is short-term rainfall prediction and is widely applied in meteorology for forecasting and disaster management. As such, the proposed hybrid architecture is better in its capacity to describe spatiotemporal data than each of the deep models that it draws upon, putting together the strengths of each architecture. Although CNN can fairly well recognize patterns within space, it is bad at handling time data, where it becomes confusing to identify long-range connections.

Keywords. Precipitation Nowcasting, Hybrid model, Weather forecasting, TCN-Bi LSTM, CNN Bi LSTM

2. INTRODUCTION

Precipitation nowcasting is short-term rainfall prediction and is widely applied in meteorology for forecasting and disaster management. The effort towards the hybrid model comprises TCN and Bi LSTM networks to enhance the outcome of precipitation nowcasting. The context from previous and future helps with the learning of Bi LSTM networks since it finds out long-range temporal dependencies while addressing the input sequence effectively.

3. METHODLOGY

This is the hybrid TCN-Bi LSTM model for precipitation nowcasting which incorporates deep architectures into capturingthe complex and intricate temporal as well as spatial relationshipsthat exist within meteorological data, leading to enhanced short- term precipitation event accuracy. It uses a combination of TCN and Bi LSTM networks wherein the strengths of both are used, thus maximizing the model's capability to recognize dependencies at both immediate as well as long ranges occurring within weather patterns. The model first accepts multivariate time-series data.

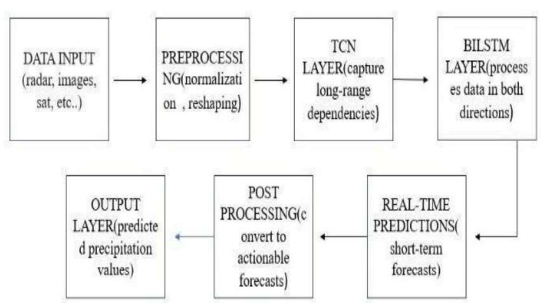

Figure 2.1-Block diagram of proposed model

These identified patterns through the process of TCN have their grounds as basic perceptions related to historical precipitation occurrences- both periodic and anomaly type of pattern. Following the TCN layer, the model will add another Bi LSTM on top that refines the temporal dependencies found in the TCN layer. This is because the Bi LSTM was specifically designed to perform that function-it scans the sequence in both directions-and it can learn dependencies spread both forward and backward from any single point in the sequence by doing so. This two-way ability of learning is quite particularly helpful in the process of precipitation nowcasting as it captures dependencies that arise due to both preceding and following weather conditions.

So, every unit of Bi LSTM has two kinds of hidden states: one for each direction; that way, the model allows it to hold on to any information that would otherwise have to be lost within a single way process. The symmetry in the flow of data ensures that the model captures the current weather patterns along with their potential repercussions in the short term. Once the data has passed through both layers of TCN and Bi LSTM, it proceeds to the output layer. An output layer is implemented as a fully connected layer that would produce a forecast value. Such a layer maps the final processed sequence onto a scalar or vector representing the precipitation forecast.Thisoutput can point out to either the precipitation intensity or the probability of rainfall, based on the need of the application of forecasting. The parameters in this output layer are fine-tuned tooptimize the precision requirement of the model so that it meets the precision demands required in short-term precipitation forecasting. Using loss functions such as Mean Squared Error that minimize the error of the forecast to optimally enhance the predictive ability of the model, adjusting the weights by backpropagation is a very essential ingredient in the training procedure. Final step: post-processing towards better interpretability and more directly usableness for the user in using the results of the forecasting. This might mean to put intensities of precipitation into bins (light, moderate, heavy) or generating probability scores that measure the likelihood of precipitation within a time window.
The TCN layer captures the long range in time through dilations in the dilation process. Dilation enhances the receptive field beyond normal CNN without its depth increase. During thisprocess, the network is likely to take patterns based on large time spans into consideration. In each of the convolutional layers, the model is applying filters to time- series data and finding repeating patterns that are associated with specific weather events. TCNs are designed as causality-preserving models. The model reads the sequence of data without referring to future time steps. This is why it's useful for predictive tasks. Dilated convolutions enable the model to carry important information across more than one time step and capture both short-time fluctuations and long-time trends of the precipitation data necessary to produce the accurate nowcasting. The output resulting from the TCN layer is further processed through the Bi LSTM layer, elaborating the forward and backward temporal information. The bidirectionality of the Bi LSTM is useful in the analysis of weather patterns because the model may learn not only past dependencies but also more general, temporal context for every time step.

The fully connected output layer then processes the data following that passed through the TCN and Bi LSTM layers. This layer yields the final numbers of the precipitation forecast. For this paper, the output can either be categorical values, which denote the possibility of falling within a specified time frame or otherwise, or continuous values that show the amounts of rain. The output layer utilized is a fully connected output layer, transforming processed data into a predicted precipitation value following the TCN and Bi LSTM layers. This dense layer aggregates the output of Bi LSTM and provides the last forecast containing actionable information such as the probability or expected intensity of precipitation. It usually accepts fine-tuning depending on the specifics of the task of precipitation nowcasting - in other words, such an optimization ofa model for a short horizon of forecasting, like one to six hours ahead. Post-processing of model outputs after generating a forecast transforms the prediction into forms useful to the end-users. For example, the model may sort the precipitation into intensity classes or probability bands so it might be interpreted easily for sectors reliant on accurate information about the weather like aviation or agriculture. It transforms raw model output to a form useful for real-time decisions. This hybrid model can also be employed with real-time input, reading fresh weather data, and producing updated forecasts of precipitation. This complementary strength in the two network types then renders the model robust in making precipitation nowcasting applicable.

The capability of capturing extended temporal dependencies with minor computational overhead from a TCN, in combination with a Bi LSTM that improves the predictions with the awareness of bidirectional temporal contexts, forms a powerful forecaster that could give short-term precipitation trends in comprehensive and real-time detail-to support accuracy and timeliness for applications in which the weather plays a significant part. The methodology behind thehybrid TCN-Bi LSTM model is such that it will deal with the inherent complexity within the precipitation nowcasting by combining peculiar strengths of TCN and Bi LSTM networks.

4. RESULTS AND DISCUSSIONS

4.1 Training and Validation Loss

The analysis of the learning curves during training and validation also provides insights into the models' behaviors, this is depicted in Fig. 2. The hybrid model demonstrated faster convergence and maintained lower validation loss compared to the CNN and BI LSTM models.

The given charts illustrate a hybrid deep learning model's performance and convergence during training by showcasing the patterns in training and validation loss throughout several epochs. The model successfully learns the underlying patterns in the data, as seen by the first graph's sharp decline in training and validation loss during the first few epochs. The training and validation loss curves converge and stabilize throughout the course of the epochs, indicating that the model has achieved an ideal state free from overfitting and underfitting. This behaviour is indicative of good regularization and a well-tuned learning process. The second graph shows that the model generalizes well to unknown data because the training and validation loss curves are almost the same throughout the training procedure. The gradual drop to almost zero loss values demonstrates how well the model performs by accurately capturing the dataset's temporal and spatial dependencies.

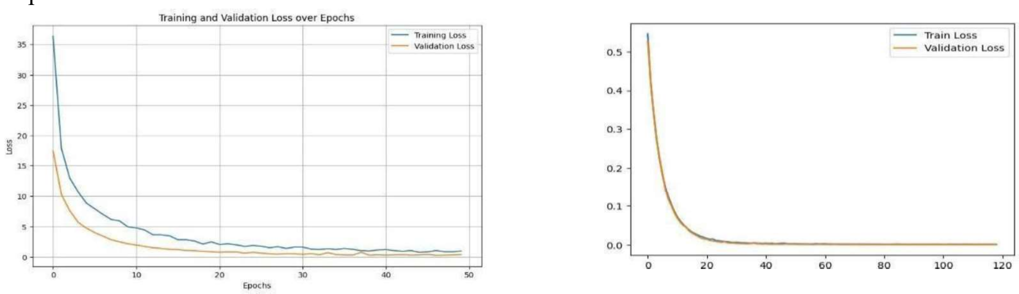

Figure 3.1- Training and validation loss

4.2 Training and Validation Accuracy

These outcomes demonstrate how well the hybrid TCN-Bi LSTM design extracts intricate features while striking a balance between generalization and training. The loss curves' quick convergence and small gap between them point to the model's stability and dependability for precise precipitation nowcasting. These performance indicators confirm that the model is appropriate for practical uses that call for accurate and reliableforecasts.

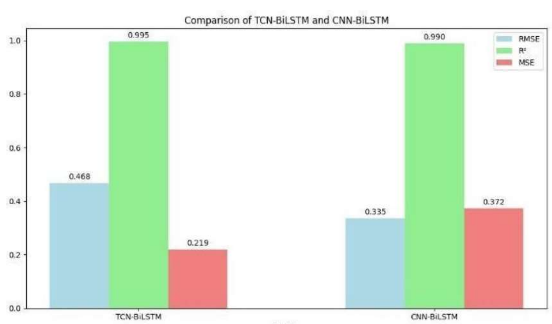

Fig. 3.2- Proposed hybrid model accuracy comparison

Using three assessment metrics—Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Coefficient of Determination (R 2)—the bar graph contrasts the performance of two hybrid deep learning models: CNN-Bi LSTM and TCN-Bi LSTM. Given the graph's lower RMSE and MSE values, which indicate improved prediction accuracy and less error, it is clear thatthe TCN-Bi LSTM model performs better than the CNN-Bi LSTM model. TCN-Bi LSTM's RMSE value is 0.468, which is substantially less than CNN-Bi LSTM's RMSE of 0.335. The TCN- Bi LSTM model can reduce errors in its predictions more successfully than CNN-Bi LSTM, as evidenced by the fact that itsMSE value (0.219) is lower than CNN-Bi LSTM's

(0.372).

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6. Biographies

Dr. B. Anjanee Kumar is an Associate Professor, Dadi Institute of Engineering and Technology, Anakapalle, Andhra Pradesh. He is currently handling many administrative and academic responsibilities. He completed his PhD., thesis titled "Optimization of Novel Design Architecture for enhancement of Lifetime in battery limited Sensor Nodes" with NIT- Warangal.

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Poojitha Nambari, Bheesetti Ruchitha, Pedireddy Venkata Satya and Madireddi Hari Krishna are final year Bachelor's students in Electronics and Communication Engineering at Dadi Institute of Engineering and Technology. Poojitha is an enthusiastic learner focused on innovation and excellence. Ruchitha and Satya are dedicated to applying their technical skills to real-world challenges. Hari Krishna is eager to grow and contribute to the field through continuous learning. Together, they strive to enhance their knowledge and make a meaningful impact in the engineering domain.