CSE541: Computer Vision

Weekly Report 3

Group - 9

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Predicting Spatio-temporal temperature variations using Machine learning models

In this experiment, 100 test cases will be divided into two sets: 60 for training and 40 for validation. The aim is to utilize AlexNet, a convolutional neural network architecture, for training. AlexNet is renowned for its effectiveness in image classification tasks, making it suitable for this experiment.

During the training phase, the 60 test cases will be used to train the AlexNet model. This process involves adjusting the model's internal parameters based on the input data (test cases) and their corresponding labels. Through iterative optimization techniques like gradient descent, the model learns to map input data to the correct output labels, which, in this case, are likely features associated with temperature prediction.

After training, the performance of the trained model will be evaluated using the remaining 40 test cases in the validation set. This validation step helps gauge the model's ability to generalize to unseen data, ensuring that it does not merely memorize the training set but learns underlying patterns that apply to new instances.

Finally, the trained AlexNet model will be employed to predict the temperature of the 101st instance. Feeding the model with relevant input data related to this instance, such as environmental factors or historical trends, will generate a prediction for the temperature. This prediction will be based on the patterns learned during the training phase, providing a practical application of the trained neural network model.

We also have integrated Long Short-Term Memory (LSTM) networks into our existing model framework to enhance its forecasting accuracy, particularly for spatiotemporal temperature fluctuations. Our primary objective was to leverage the temporal dynamics inherent in temperature data, which are well-suited to LSTM architectures due to their ability to capture long-term dependencies.

Initially, we conducted a thorough review of LSTM networks and their applicability to our forecasting task. After understanding the intricacies of LSTM architecture, we proceeded to implement it within our model pipeline. This involved modifying our existing codebase to incorporate LSTM layers alongside the pre-existing AlexNet architecture.

With the integration of LSTMs, our model gained the capability to capture and learn temporal patterns present in the temperature data, allowing for more accurate predictions of future temperature fluctuations. We conducted extensive testing and validation to ensure the seamless integration of LSTM networks and to evaluate the performance improvements achieved.