World Wide Journal of Multidisciplinary Research and Development (July-2021)

WWJMRD 2021; 7(7): 14-16
www.wwjmrd.com
International Journal
Peer Reviewed Journal
Refereed Journal
Indexed Journal
Impact Factor SJIF 2017: 5.182 2018: 5.51, (ISI) 2020-2021: 1.361
E-ISSN: 2454-6615
DOI: 10.17605/OSF.IO/NYZ2B

Abhinayaa K S
Department of Information Science & Technology, College of Engineering, Guindy, 600025, India

Bavani B
Department of Information Science & Technology, College of Engineering, Guindy, 600025, India

Dr. Indumathi J
Department of Information Science & Technology, College of Engineering, Guindy, 600025, India.

Correspondence:
Abhinayaa K S
Department of Information Science & Technology, College of Engineering, Guindy, 600025, India

Multi-Profundity soil water content prognosis for Maize

Abhinayaa K S, Bavani B, Dr. Indumathi J

Abstract
The soil water content prediction in agricultural land improved more irrigation plans and the moisture content of the soil at multiple depths elevated more extensively with numerous irrigation methods and techniques. The accuracy of foreseeing Soil Water Content at multiple depths can be amended using the BiLSTM and the ResNet model. The ResBiLSTM model together might stretch improved prediction accuracy with the meteorological and time series data of growth stages of maize. The prediction model for soil moisture at different depths embraces 5_cm, 10_cm, 20_cm, 50_cm and 100_cm respectively. The MSE, MAE, RMSE, R^2 are premeditated for predicting the finest fit accuracy at different growth stages. The values are predicted from the actual value calculated and the accuracy is found for the predicted values. The average value is calculated for the corresponding values. These average values are then compared with the other machine learning and deep learning models. Also, to attain ResBiLSTM model provides better accuracy and prediction than the usual deep learning models.

Keywords: soil water content, BiLSTM, ResNet, multi-depth and ResBiLSTM.

Introduction
Residual Network (ResNet) is used to solve the problem of the vanishing exploding gradient. BiLSTM or Bidirectional LSTM is a sequence processing model that consists of two LSTMs. Food demand, to meet enlarged human population will mount worldwide. Among the harvests, maize is a C4 crop with high productivity, and plays a vital role in food security. To improve the accuracy of predicting soil water content at multiple depths by envisaging meteorological and SWC data at all growth stages is much more important for the maize growth and its cultivation.

Objectives
- To predict SWC at multiple depths with improved accuracy.
- To extract high-dimensional spatial and time series features by using ResNet and BiLSTM.
- To develop a prediction model ResBiLSTM for soil moisture content.
- To combine data from different growth stages of summer maize.
- To analyze the autocorrelation characteristics of soil water content.

Proposed System
The proposed system determines the accuracy of foreseeing Soil Water Content at multiple depths can be amended using the BiLSTM and the ResNet model. The ResBiLSTM model together might stretch improved prediction accuracy with the meteorological and time series data of growth stages of maize. The prediction model for soil moisture at different depths embraces 5_cm, 10_cm, 20_cm, 50_cm and 100_cm respectively. The MSE, MAE, RMSE, R^2 are premeditated for predicting the finest fit accuracy at different growth stages. Thus, to improve the accuracy of predicting soil water content at multiple depths by envisaging meteorological and SWC data at all growth stages is much more important for the maize growth and its cultivation.

Bidirectional LSTM Model
The forward LSTM and the backward LSTM combined together forms the BiLSTM structure. BiLSTM uses ReLU function to avoid overfitting. The input in the BiLSTM block is flattened and this is fed to the consecutive BiLSTM layers and output to a fully connected layer which consists of 64 filters. BiLSTM provides better time domain feature representations. The gradient explosion can be abolished by the memory unit by retaining the important information and disremembering unimportant information.

ResNet model
Residual block is the core module of the ResNet. This ResNet is built on convolutional arithmetic to extract informative features. The problem of gradient disappearing is solved by directly connecting the gradient in the residual block to early layer.

ResBiLSTM model
The spatio-temporal features are extracted by integrating the two branches of ResBiLSTM model. To achieve better data fitting competences the extracted features are learnt by a meta-learner. The input for the ResNet and the BiLSTM branch includes the soil water content data and time series data.

Results & Discussion
From the BiLSTM model built and the various techniques performed could determine the accuracy for the soil water content at multiple depths according to the growth stages. Compared to deep related study models, the ResBiLSTM model shows better predictive accuracy. As SWC is directly affected by irrigation and rainfall, precarious rainfall creates opportunities for SWC affected by the increase in rainfall over the number of days delayed, which increases the difficulty of accurate prediction by model. The training accuracy achieved with model is 0.48799 and the test accuracy achieved for the actual and the predicted values is 0.55186 respectively. The co-efficient determination obtained for the model is 0.5546439. The co-efficient achieved by the BiLSTM model for actual and prediction is 0.542950 and 0.533294 respectively.

Tables and Figures - implementing ResBiLSTM
The ResBiLSTM model is built in the google colab using the python code. This helps to perform prediction and accuracy for the given data. The ResBiLSTM model with train loss and test loss value is shown in Fig 1.

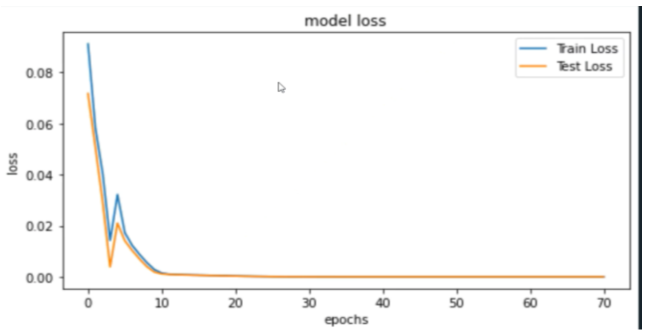

Fig 1: train and test loss graph.

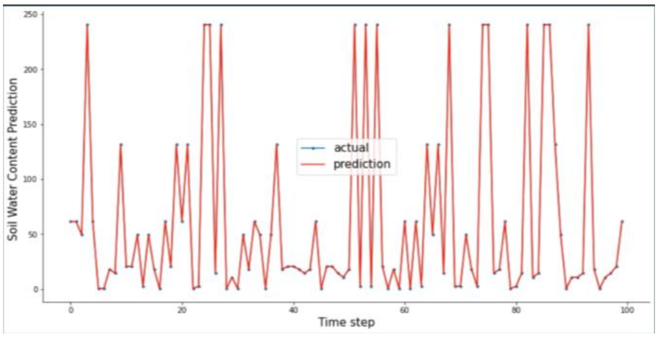

Fig 2: actual and prediction value graph.

The actual and prediction graph for the provided data using ResBiLSTM model is shown in Fig 2. respectively.

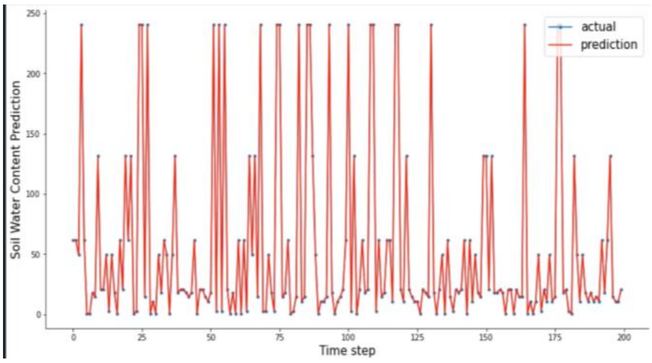

Fig 3: actual and prediction value graph.

The actual and prediction graph for the provided data using ResBiLSTM model is shown in Fig 3 respectively.

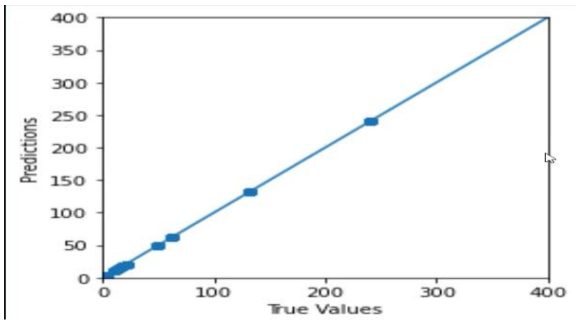

Fig 4: true value graph.

The ResNet model with true value prediction is shown in Fig 4.

Equations - Loss Functions
Various loss functions are calculated in this model to indicate the performance. The formulas for the loss functions are as follows.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \quad (1)$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|(y_i - \hat{y}_i)| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \quad (3)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (4)$$

$$R^2 = 1 - \frac{\Sigma_i (\hat{y}_i - y_i)^2}{\Sigma_i (\bar{y}_i - y^i)^2} \quad (5)$$

were,

y_i – estimated value

$\hat{y}_i$ – observed value

$\bar{y}_i$ – average value

Conclusions

This project deals with the prediction of soil water content at multiple depths of the soil. The accuracy is calculated by combining BiLSTM and ResNet model. The ResBiLSTM model achieve better accuracy than getting the accuracy separately. Better data fit is achieved at different growth stages. The proposed ResBiLSTM model has the great advantage of predicting more accuracy than traditional machine learning models (SVR, MLP and RF). Compared to deep related study models, the ResBiLSTM model shows better predictive accuracy.

References

1. B. Ait Hssaine, O. Merlin, J. Ezzahar, S. Er-raki, S. Khabba, and A. Chehbouni, ''Assessing soil moisture constraint on soil evaporation and plant transpiration fractioning,'' in Proc. EGU Gen. Assem. Conf. Abstr., p. 8751, 2020.
2. C. C. Hongsong, ''Study on construction of IOT network intrusion detection classification model and optimization based on combination of ResNet and bidirectional LSTM network,'' J. Hunan Univ. Nat. Sci., vol. 47, no. 8, pp. 1–8, 2020.
3. J. Zhang, F. Chen, Z. Cui, Y. Guo, and Y. Zhu, ''Deep learning architecture for short-term passenger flow forecasting in urban rail transit,'' IEEE Trans. Intell. Transport. Syst., early access, doi: 10.1109/TITS.2020.3000761, 2020.
4. J. Zhou, Y. Lu, H.-N. Dai, H. Wang, and H. Xiao, ''Sentiment analysis of Chinese microblog based on stacked bidirectional LSTM,'' IEEE Access, vol. 7, pp. 38856–38866, 2019.
5. K. He, X. Zhang, S. Ren, and J. Sun, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), pp. 770–778, 2016.
6. K. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, ''Machine learning in agriculture: A review,'' Sensors, vol. 18, no. 8, p. 2674, 2018.
7. M. K. Saggi and S. Jain, ''Application of fuzzy-genetic and regularization random forest (FG-RRF): Estimation of crop evapotranspiration (ET) for maize and wheat crops,'' Agricult. Water Manage., vol. 229, Art. no. 105907, doi: 10.1016/j.agwat.2019.105907, 2020.
8. O. Adeyemi, I. Grove, S. Peets, Y. Domun, and T. Norton, ''Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling,'' Sensors, vol. 18, no. 10, p. 3408, doi: 10.3390/s18103408, 2018.
9. T. Li, M. Hua, and X. Wu, ''A hybrid CNN-LSTM model for forecasting particulate matter (PM2.5),'' IEEE Access, vol. 8, pp. 26933–26940, doi: 10.1109/ACCESS.2020.2971348, 2020.
10. W. Zheng, L. Zhangzhong, X. Zhang, C. Wang, S. Zhang, S. Sun, and H. Niu, ''A review on the soil moisture prediction model and its application in the information system,'' in Computer and Computing Technologies in Agriculture XI. Cham, Switzerland: Springer, pp. 352–364, doi: 10.1007/978-3-030-06137-1_32, 2019.
11. Y. Cai, W. Zheng, X. Zhang, L. Zhangzhong, and X. Xue, ''Research on soil moisture prediction model based on deep learning,'' PLoS ONE, vol. 14, no. 4, Art. no. e0214508, doi: 10.1371/journal.pone.0214508, 2019.
12. Z. Hong, Z. Kalbarczyk, and R. K. Iyer, ''A data-driven approach to soil moisture collection and prediction,'' in Proc. IEEE Int. Conf. Smart Comput. (SMARTCOMP), pp. 1–6, 2016.