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Original Article

Smart Irrigation System based on Spatial Temporal Convolution Long Short Term Memory for Forecasting of Temperature and Humidity

A. Venkateshwar[1], Venkanagouda C. Patil[1]

[1]*Department of Computer Science and Engineering, Ballari Institute of Technology and Management, Karnataka, India.*

[1] venkateshwar@bitm.edu.in

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Abstract *- Smart irrigation system and the Internet of Things (IoT) is used in agriculture to preserve water and improve crop productivity. Various pieces of research were carried out for smart irrigation using IoT and have limitations of outlier and lower performance. This research uses the Spatial Temporal – Convolutional Long Short Term Memory (ST-ConvLSTM) model to improve the efficiency of predicting temperature and humidity. Dataset collected from sensors was applied to evaluate the ST-ConvLSTM model in a smart irrigation system. The convolutional layer preserves the spatial information and applies to temperature and humidity forecasting. The temporal information of relevant information is stored in LSTM for the long term to increase the effectiveness of the prediction. The RMSE of the proposed ST-ConvLSTM model has 0.77 RMSE, and K Nearest Neighbor (KNN) has an RMSE of 1.53.*

Keywords *- Convolutional Layer, Internet of Things (IoT), Spatial Information, Spatial Temporal – Convolutional Long Short Term Memory, and Temporal Information.*

1. Introduction

Precision agriculture and smart farming integrate advanced technologies into existing framing practices to increase agricultural product quality and production efficiency. Quality of life is improved for farmworkers by reducing tedious tasks and heavy labor [1]. Wireless Sensor Networks (WSN) and Internet of Things (IoT) in precision agriculture have used natural resources more effectively based on a collection of air quality, weather, soil, and crop development to assist farmers and agriculture workers in intelligent decision-making related to harvesting crops, fertilizing, and planting [2]. The country's economy and revenue are highly based on agriculture. Various reasons include improper electric supply in rural areas and crops' lack of water affecting agriculture [3]. The irrigation system applied in the existing method for deployment requires IoT nodes' environmental data that is remotely activated using intelligent automated actions and manual commands [4]. A growing population has increased the demand for global food, increasing pressure on water resources [5].

Key factors of agriculture are evaporation and precipitation, which influence soil moisture. The soil wetness is measured by annual evaporation and precipitation in climatology and geography [6]. If a good crop yield is required, then the irrigation system requires monitoring, especially in water scarcity areas. Farming operations face challenges related to energy for a good yield of crops. Agriculture efficiency is widely researched from several viewpoints [7, 8]. In the last ten years, the groundwater level has gradually decreased, and a poor monsoon exists. Automation in irrigation systems is required for water resources, and most research concentrates on the automation of irrigation systems [9, 10]. Existing methods have limitations of vanishing gradient problem and are sensitive to outlier that affects the model's efficiency. Existing models have lower efficiency in handling the Spatio-temporal features of the input data. The objectives and contribution of this research are discussed as follows:

1. ST-ConvLSTM model forecasts temperature and humidity based on IoT sensor data. The Convolution layer effectively analyses the input data's spatial information, and the LSTM layer is applied for forecasting.
2. The ST-ConvLSTM model achieves higher performance in forecasting than the existing model due to its efficiency in handling spatial information.

This paper is formulated as follows: Section 2 provides a Literature review, and Section 3 provides the proposed method. The result and discussion are provided in Section 4, and the conclusion is given in Section 5.

2. Literature Review

Smart irrigation systems based on IoT devices improved crop cultivation and productivity. Various kinds of research were carried out for smart irrigation systems based on machine learning methods for predicting rainfall.

Goap et al. [11] developed a smart system based on open source technology for irrigation prediction using ground parameter sensing like environmental condition, soil temperature and soil moisture. The sensing of environment and ground is based on sensing nodes like relative humidity, Ultraviolet (UV) light radiation, air temperature, soil temperature, and soil moisture. The developed system performs a forecast of weather parameters like humidity, perception, air temperature, and UV. A fully automatic irrigation system realizes water supply in a closed loop of water supply control. Support Vector Regression (SVR) and K-means algorithms were proposed to perform the prediction of parameters. The SVR method has an imbalance data problem, and the K-Means method has random initialization.

Krishnan et al. [12] applied a fuzzy logic controller to compute input parameters like humidity, temperature and soil moisture. The developed method produces the outputs of motor status. The system switches off the motor when there is rain to save power and also protects the crop using a panel when there is unconditional rain. The developed method shows the efficiency of the irrigation process compared to manual irrigation. The fuzzy method has lower performance in the prediction process due to its rule generation process.

Nawandar and Satpute [13] developed IoT based smart irrigation system using a neural network to monitor and predict the parameters. The complex season irrigation schedule was measured in the developed method. The irrigation unit alerts the system for the watering zone wise, and the MQTT broker was used to send sensor data for remote monitoring. The 2-layer neural network was applied for the decision process based on the input parameters from the IoT device. The neural network model has the limitation of data imbalance and overfitting problems.

Ullah et al. [24] applied energy-efficient water management systems using open source cloud, fusion centres, sinks and field-deployed sensors based on IoT devices. Packet delivery ratio, the packet sent to destination, network stability period, and Energy consumption was used to evaluate the model. The simulation is carried out to test the performance of the developed-in smart irrigation system. It shows that the developed method has 30 % less energy consumption compared to the existing model in the smart irrigation system.

Munir et al. [15] developed a smart irrigation system using ontology for 50 % of the decision, and 50 % decision is based on sensor data. The K-Nearest Neighbour (KNN) machine learning method is used for final decisions using sensor data and ontology data. The machine learning method is used in this study to decide the water requirement for a particular plant. An edge server is applied between the GSM module and the IoT server. This method reduces sever processing of data and reduces the latency rate of the system. The KNN model is sensitive to outlier data that affects the efficiency of the classification.

3. Proposed Method

A smart irrigation system based on an IoT device is required in Agriculture to improve crop production. Spatial information is preserved in the Convolution layer to preserve the information, and temporal information is applied in LSTM. The spatial and temporal information is preserved in the LSTM model to handle the time series data effectively. The LSTM model stores the long-term relevant features and increases the classification's efficiency. The model's attention technique selects the features and gives higher weight to the relevant features. The ST-ConvLSTM model flow is shown in Figure 1.

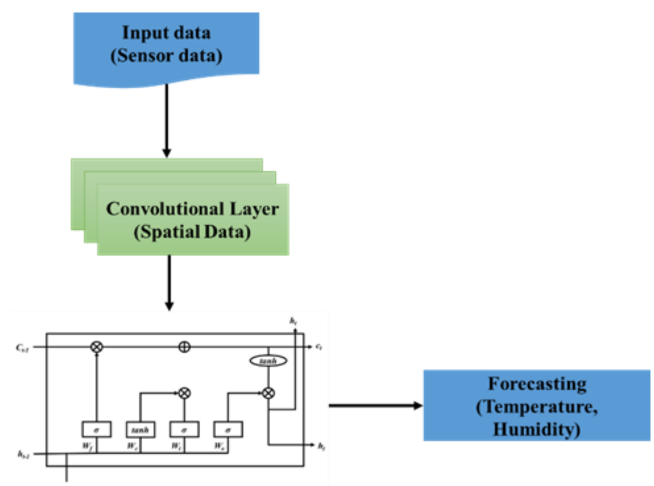

Fig. 1 The block diagram of proposed ST-ConvLSTM

3.1. Convolutional Layer

The spatial features are extracted in this layer. The convolutional layer convolves input feature data x, and the receptive field is covered over each convolutional kernel. As given in equation (1), convolution layers are adjusted with variables.

$$\overline{x}_l = g(\textstyle\sum_{m \in M_i} x_i \times k_{mi} + b_{mi}), 1 \leq i \leq w \quad (1)$$

Where corresponding convolution kernel bias and learnable weight are denoted as $b_{mi} and k_{mi}$ inputs selection is denoted as M_i convolution layer output is x_i $(x = x_1, x_2, x_3, \ldots w))$ convolution layer of non-linear activation function is denoted as $g()$. Nearby values of complex dependencies are applied in a convolution layer that is exploited effectively.

3.2. Temporal Correlation Extraction

The attention model of the two-stage effectively excludes irrelevant attribute information that selects a series of the relevant driver to apply great weight to it and target a series of past input values, further eliminating interference of less useful information. LSTM with the attention method effectively solves long-term time dependence problems in prediction.

The convolution layer is processed in the stage of attention Layer, $\overline{x} = (\overline{x}_1, \overline{x}_2, \ldots, \overline{x}_w)$in the attention layer. Mapping from $\overline{x}$to a of the attention method (at time step w) is given in equation (2).

$$a = f_1(h_w, s_w, \overline{x}) \qquad (2)$$

Where the attention layer of the non-linear activation function is $f_1(.)$, the first LSTM hidden layer is $h_w = (h_1, h_2, \ldots h_w)$, and the current output value is $S_w = (S_1, S_2, .. S_w)$. The formula is as follows in equation (3).

$$\begin{cases} e_i = v_e^T\, tanh(\, W_c[h_w : s_w] + U_e \overline{x}_i) & 1 \leq i \leq w \\ a_i = (exp(\, e_i))/(\sum_{i=1}^{w} exp(\, e_i)) & 1 \leq i \leq w \end{cases} \qquad (3)$$

Where each time step of corresponding attention weight is denoted as $\alpha_i, h_w and w_s$concatenation is given in $[h_w; s_w]$, attention mechanism is learned based on parameters of v_e, W_e, U_e. Lack of long-term time-dependent attention mechanism can assign weights of LSTM to its input based on LSTM internal parameters.

3.3. Long Short Term Memory

The LSTM can retain important information for the long term based on cell and forget gate. The classification of arrhythmia signals requires not only recent data but also previous data. A self-feedback method in a hidden layer handles the problem of long-term dependence in the LSTM model [16, 17]. Three gates and memory cells store LSTM information for long-term features [18 - 23]. The cell of the Bi-LSTM model is shown in Figure 2.

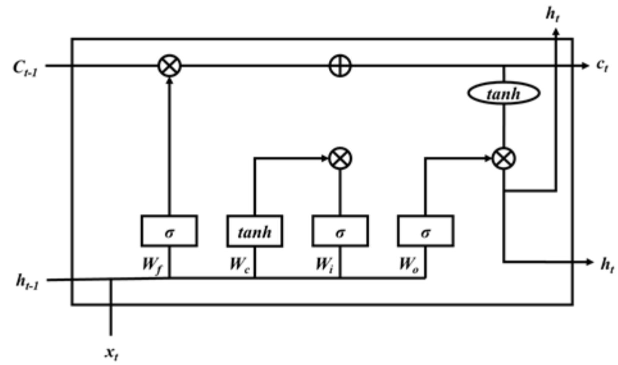

Fig. 2 LSTM unit architecture

The output cell of LSTM's previous moment is $h_{t-1}$the value of a memory cell C_t, and the output cell of LSTM is h_t and x_t at the time t is input data to the LSTM cell. The LSTM unit calculation process is explained in steps.

1. The weight matrix is W_c, bias is b_c, the candidate memory cell is $\overline{c}_t$, as shown in equation (4).

$$\tilde{c}_t = tanh(\, W_c . [h_{t-1, x_t}] + b_c) \qquad (4)$$

2. The sigmoid function is σ, the input gate $i_t$and the bias is b_i, the weight matrix W_i. The input gate controls the current input state value of the memory cell state, as shown in equation (5).

$$it = \sigma(W_i . \left[h_{t-1, x_t}\right] + b_i) \qquad (5)$$

3. The bias is b_f, the weight matrix is W_f, forget gate updates historical data in state value of memory cell, and forget gate isf_t, as given in equation (6).

$$f_t = \sigma(W_i . [h_{t-1}, x_t] + b_f) \qquad (6)$$

4. The state value of the previous LSTM unit is c, and the memory cell of the current moment$c_t$is calculated, as given in equation (7).

$$c_t = f_t * c_t - 1 + i_t * \tilde{c}_t \qquad (7)$$

Where '*' denotes the dot product. Forget and Input gate controls to update the state value memory cell based on the candidate and last cell.

5. The weight matrix is W_0, bias isb_0, output gate of output memory state value, and output gate is o_t, which is given in equation (8).

$$o_t = \sigma(W_0.[h_{t-1}, x_t] + b_0) \quad (8)$$

6. The output h_t of the LSTM unit is as given in equation (9).

$$h_t = o_t * tanh(c_t) \quad (9)$$

LSTM model update, reset, read and keep long-time information easily based on memory cell and control gates. The LSTM model sharing mechanism of internal parameters controls the output dimensions based on weight matrix dimensions' settings.

4. Result

Smart irrigation systems based on IoT devices were required in agriculture to improve crop productivity. The sensor data is input to the model, which predicts the temperature and humidity.

Table 1. Temperature forecast based on proposed ST-ConvLSTM

Date	SVR-Kmeans [11]	Fuzzy Logic [12]	Neural Network [13]	KNN [15]	LSTM	ST-ConvLSTM
01-12-2020	2.39	1.76	1.81	1.43	1.17	0.31
02-12-2020	2.88	1.69	1.64	1.52	1.09	0.53
03-12-2020	2.3	2.27	1.94	1.2	1.03	0.39
04-12-2020	2.24	2.37	1.53	1.42	1.09	0.51
05-12-2020	2.94	1.57	1.97	1.46	1.1	0.69
06-12-2020	2.78	1.72	1.88	1.35	1.1	0.55
07-12-2020	2.84	2.27	1.84	1.48	1.19	0.64
08-12-2020	2.39	2.02	1.6	1.2	1.15	0.38
09-12-2020	2.15	1.97	1.83	1.55	1.13	0.54
10-12-2020	2.8	2.07	1.64	1.42	1.17	0.77
11-12-2020	2.55	1.93	1.81	1.4	1.01	0.78
12-12-2020	2.9	1.51	1.96	1.46	1.11	0.5
13-12-2020	2.64	2.33	1.63	1.29	1.18	0.5
14-12-2020	2.58	2.22	1.98	1.23	1.11	0.56
15-12-2020	2.63	2.21	1.8	1.28	1.18	0.6
16-12-2020	2.3	1.94	1.58	1.3	1.1	0.42
17-12-2020	2.2	1.5	1.95	1.2	1.09	0.57
18-12-2020	2.08	1.53	1.81	1.54	1.14	0.72
19-12-2020	2.04	1.7	1.6	1.33	1.13	0.71
20-12-2020	2.21	1.91	1.94	1.43	1.05	0.51
21-12-2020	2.66	2.1	1.85	1.26	1.11	0.65
22-12-2020	2.56	2.02	1.77	1.45	1.06	0.76
23-12-2020	2.59	2.17	1.68	1.26	1.2	0.58
24-12-2020	2.82	1.85	1.8	1.36	1.19	0.36
25-12-2020	2.45	2.24	1.78	1.56	1.18	0.71
26-12-2020	2.57	2.39	1.64	1.24	1.07	0.38
27-12-2020	2.56	1.67	1.58	1.53	1.12	0.31
28-12-2020	2.03	2.38	1.54	1.25	1.18	0.56
29-12-2020	2.46	2.29	1.55	1.23	1	0.75
30-12-2020	2.71	1.9	1.84	1.53	1.02	0.77

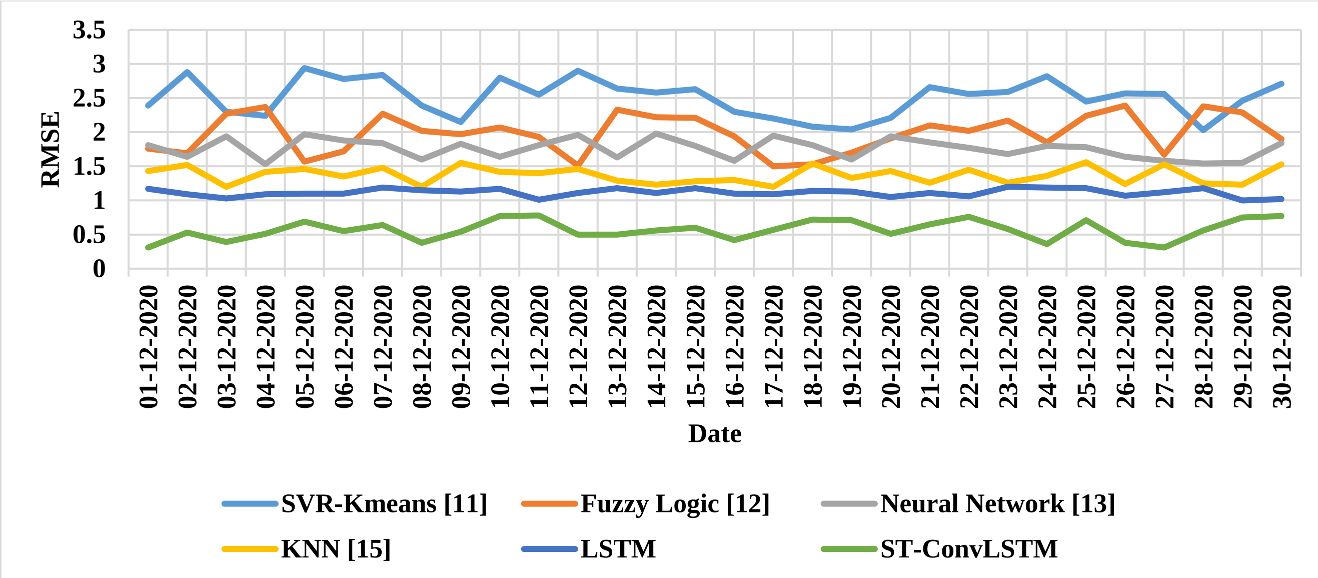

Fig. 3 RMSE of Temperature forecast based on proposed ST-ConvLSTM

The proposed ST-ConvLSTM model RMSE is compared with existing methods, as shown in Figure 3 and Table 1. The ST-ConvLSTM model has a lower error value than existing methods due to the advantage of the spatial-temporal model. The existing LSTM model has a limitation of vanishing gradient problem and degrades the performance. The KNN model is sensitive to outlier data and has lower efficiency in handling the outlier data. The proposed model considers spatial data for convolution, and temporal data is applied in the LSTM classifier. The proposed ST-ConvLSTM model has the advantage of preserving the spatial and temporal information that is useful for classification.

Table 2. The proposed method MSE of the temperature forecast

Date	SVR-Kmeans [11]	Fuzzy Logic [12]	Neural Network [13]	KNN [15]	LSTM	ST-ConvLSTM
01-12-2020	1.55	1.33	1.35	1.20	1.08	0.56
02-12-2020	1.70	1.30	1.28	1.23	1.04	0.73
03-12-2020	1.52	1.51	1.39	1.10	1.01	0.62
04-12-2020	1.50	1.54	1.24	1.19	1.04	0.71
05-12-2020	1.71	1.25	1.40	1.21	1.05	0.83
06-12-2020	1.67	1.31	1.37	1.16	1.05	0.74
07-12-2020	1.69	1.51	1.36	1.22	1.09	0.80
08-12-2020	1.55	1.42	1.26	1.10	1.07	0.62
09-12-2020	1.47	1.40	1.35	1.24	1.06	0.73
10-12-2020	1.67	1.44	1.28	1.19	1.08	0.88
11-12-2020	1.60	1.39	1.35	1.18	1.00	0.88
12-12-2020	1.70	1.23	1.40	1.21	1.05	0.71
13-12-2020	1.62	1.53	1.28	1.14	1.09	0.71
14-12-2020	1.61	1.49	1.41	1.11	1.05	0.75
15-12-2020	1.62	1.49	1.34	1.13	1.09	0.77
16-12-2020	1.52	1.39	1.26	1.14	1.05	0.65
17-12-2020	1.48	1.22	1.40	1.10	1.04	0.75
18-12-2020	1.44	1.24	1.35	1.24	1.07	0.85
19-12-2020	1.43	1.30	1.26	1.15	1.06	0.84
20-12-2020	1.49	1.38	1.39	1.20	1.02	0.71
21-12-2020	1.63	1.45	1.36	1.12	1.05	0.81
22-12-2020	1.60	1.42	1.33	1.20	1.03	0.87
23-12-2020	1.61	1.47	1.30	1.12	1.10	0.76
24-12-2020	1.68	1.36	1.34	1.17	1.09	0.60

25-12-2020	1.57	1.50	1.33	1.25	1.09	0.84
26-12-2020	1.60	1.55	1.28	1.11	1.03	0.62
27-12-2020	1.60	1.29	1.26	1.24	1.06	0.56
28-12-2020	1.42	1.54	1.24	1.12	1.09	0.75
29-12-2020	1.57	1.51	1.24	1.11	1.00	0.87
30-12-2020	1.65	1.38	1.36	1.24	1.01	0.88

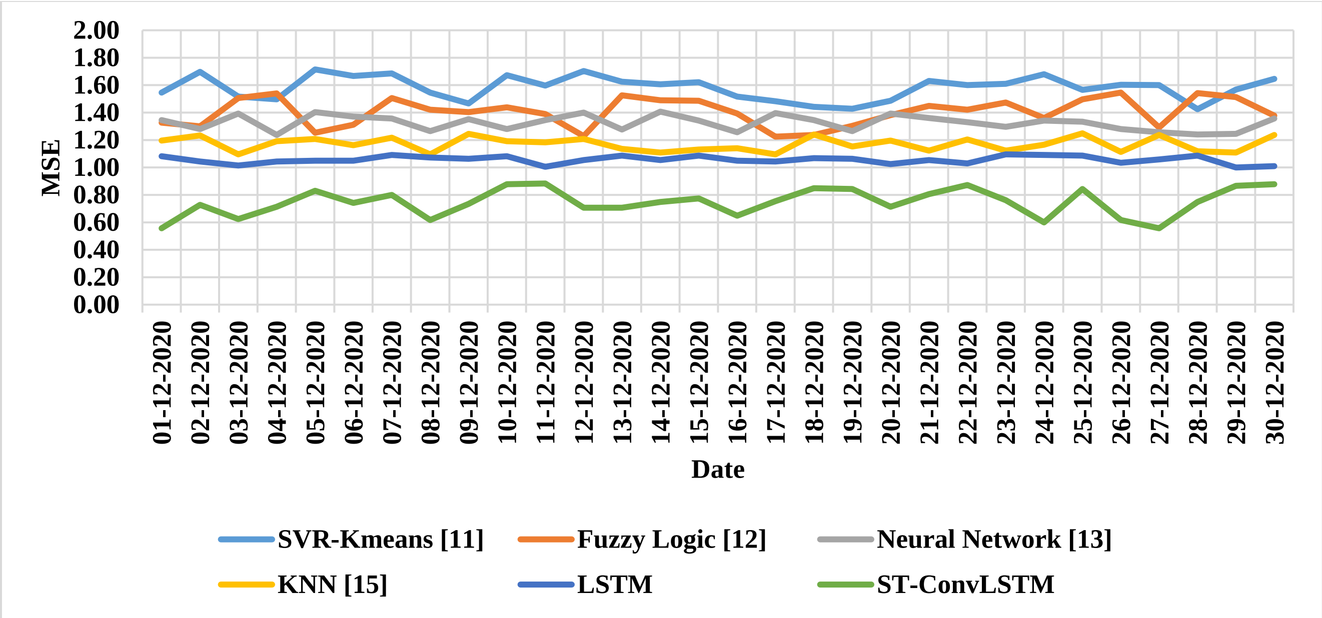

Fig. 4 The proposed method MSE of the temperature forecast

The MSE value of the proposed method is measured for temperature forecast and compared with existing techniques, as shown in Figure 4 and Table 2. The ST-ConvLSTM method has a lower error rate in forecasting due to its advantage of preserving spatial and temporal information. The SVR-Kmeans has an imbalance data problem, and fuzzy logic has unstable performance in the classification. A neural network has a problem overfitting the prediction, and the KNN model is sensitive to the outlier. The LSTM model has a second higher performance due to its capacity to store long-term relevant information.

Table 3. Humidity forecast of the proposed ST-ConvLSTM model

Date	SVR-Kmeans [11]	Fuzzy Logic [12]	Neural Network [13]	KNN [15]	LSTM	ST-ConvLSTM
01-12-2020	4.13	3.86	2.98	2.27	1.22	0.57
02-12-2020	4.03	3.7	2.94	1.82	1.54	0.7
03-12-2020	4.4	3.12	2.79	2.26	1.78	0.73
04-12-2020	4.34	3.37	3.2	2.4	1.33	0.73
05-12-2020	4.13	3.94	2.91	2.21	1.86	0.77
06-12-2020	4.61	3.84	3.08	1.98	1.09	0.43
07-12-2020	4.15	3.21	3.25	2.34	1.5	0.68
08-12-2020	4	3.08	3.28	2.2	1.98	0.5
09-12-2020	4.71	3.75	2.7	2.19	1.37	0.69
10-12-2020	4.01	3.5	3.33	1.92	1.97	0.7
11-12-2020	4.76	3.26	2.67	1.91	1.28	0.57
12-12-2020	4.82	3.56	2.94	2.18	1.35	0.58
13-12-2020	4.21	3.02	3.07	1.95	1.8	0.71
14-12-2020	4.22	3.86	2.94	1.99	1.75	0.52
15-12-2020	4.5	3.67	3.04	1.82	1.38	0.3
16-12-2020	4.38	3.09	3.2	1.92	1.85	0.55
17-12-2020	4.93	3.67	3.01	2.11	1.19	0.68

18-12-2020	4.36	3.83	3	2.38	1.25	0.4
19-12-2020	4.28	3.78	2.79	2.23	1.63	0.34
20-12-2020	4.2	3.42	2.92	1.91	1.09	0.39
21-12-2020	4.87	3.27	2.67	1.98	1.02	0.47
22-12-2020	4.44	3.78	2.6	2.36	1.7	0.65
23-12-2020	4.55	3.35	3.23	2.15	1.07	0.73
24-12-2020	4.33	3.82	3.18	2.05	1.1	0.35
25-12-2020	4.44	3.41	3.14	1.98	1.3	0.69
26-12-2020	4.85	3.61	2.68	1.81	1.78	0.48
27-12-2020	4.23	3.31	3.33	2.31	1.2	0.71
28-12-2020	4.73	3.31	2.65	2.2	1.12	0.76
29-12-2020	4.66	3.72	3.14	1.9	1.73	0.59
30-12-2020	4.83	3.29	3.06	1.97	1.62	0.8

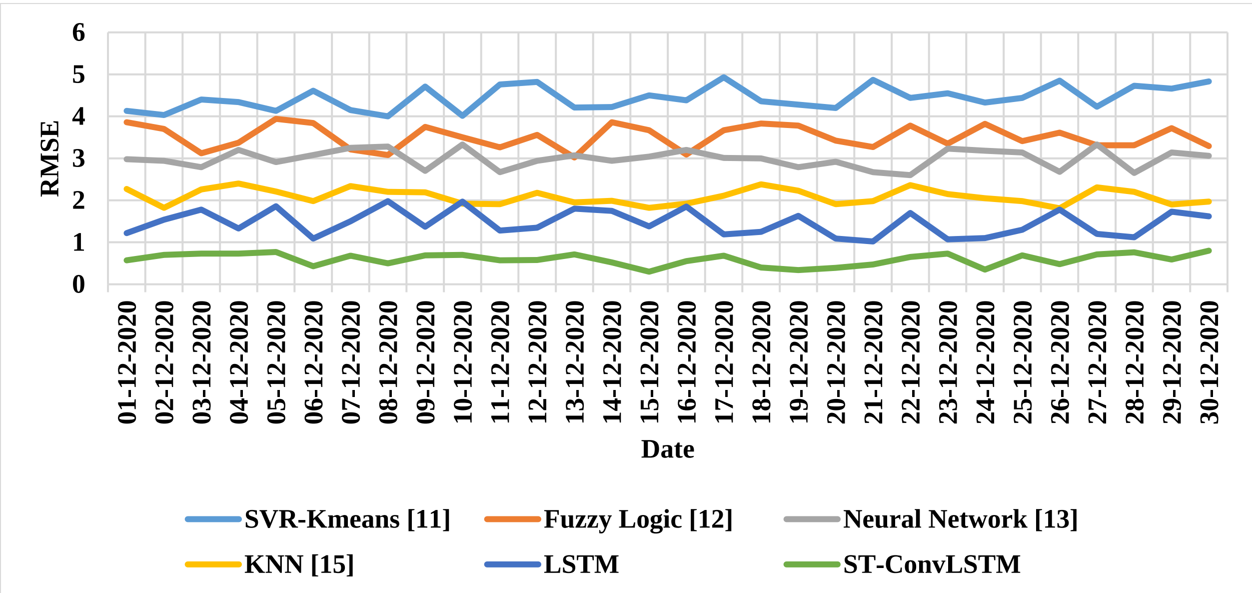

Fig. 5 Proposed method RMSE for humidity prediction

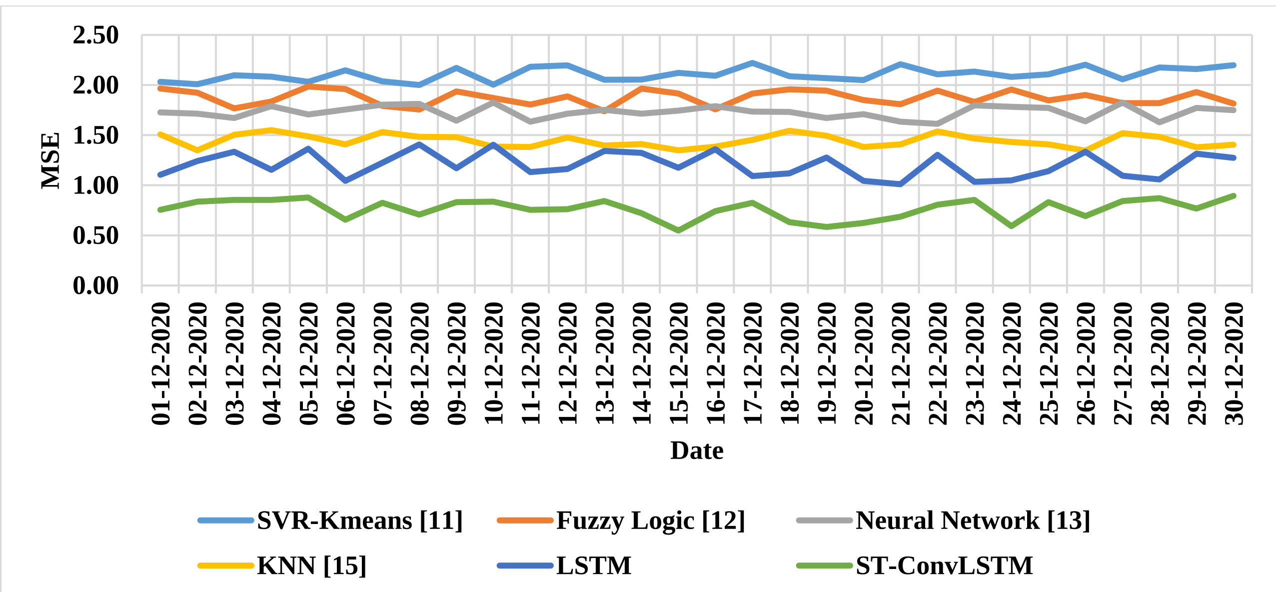

Fig. 6 MSE of proposed method humidity forecasting

The humidity forecast of ST-ConvLSTM is measured in RMSE and compared with existing methods, as shown in Figure 5 and Table 3. The ST-ConvLSTM method has a lower error rate than an existing method in humidity forecasting. The LSTM has a second higher performance due to its efficiency in storing related information for the long term. The existing LSTM model has a vanishing gradient problem and KNN model is sensitive to outlier data instances that degrade the model's efficiency. The ST-ConvLSTM method has the advantage of preserving the spatial and temporal information that helps to improve forecasting performance.

The proposed method MSE of humidity forecasting is compared to the existing methods such as Neural network and KNN, as shown in Figure 6. The ST-ConvLSTM method has a lower error than the existing method in humidity forecasting. The SVR-Kmeans method has an imbalance data problem, and Fuzzy logic has unstable performance. The neural network has an overfitting problem, and the KNN model is sensitive to outlier performance. The ST-ConvLSTM method has the advantage of preserving the spatial and temporal information that helps to improve the prediction performance.

5. Conclusion

Smart irrigation uses sensor devices to monitor the temperature, humidity and water level for prediction. Various existing methods were applied for the smart irrigation system, limiting outlier and lower performance. This research applies the SL-ConvLSTM model to increase the efficiency of forecasts. The SL-ConvLSTM has the advantage of preserving spatial and temporal information for the prediction process. The ST-ConvLSTM model has 0.77 RMSE, and K Nearest Neighbor (KNN) has 1.53 RMSE in forecasting. The result shows that the SL-ConvLSTM has higher forecasting efficiency than existing methods. The KNN model limits sensitivity to outliers, and the Neural network faces an overfitting problem in prediction. The future work of this research involves applying an optimization-based feature selection process for temperature and humidity prediction.

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