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RESEARCH ARTICLE

Context Aware Evapotranspiration (ETs) for Saline Soils Reclamation

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ABSTRACT Accurate Evapotranspiration for saline soils (ETs) is important as well as challenging for the reclamation of saline soils through an effective leaching process. Evapotranspiration (ET) by FAO-56 Penman-Monteith standard method is complex, especially for saline soils. Moreover, existing studies focus on the use of the Internet of Things (IoT) and machine learning-enabled smart and precision irrigation water recommendation systems along with the ET estimation by limited parameters. The ETs for saline soils are also equally important for the reclamation of saline soils, which is ignored by the existing literature. The study proposed IoT and machine leaching-based architecture of context-aware monthly ETs estimations for saline soil reclamation with the effective leaching process. The IoT-enabled crop field contexts in terms of crop field temperature, soil salinity, and irrigation water salinity are used as input features to the Long Short-Term Memory (LSTM) and ensembled LSTM models for monthly ETs predictions. The performance of the proposed solution is observed in terms of the accuracy of the machine learning models along with the comparison against the FAO-56 PM-based standard method. The implementation of the proposed solution reveals that the ensembled LSTM-based approach for ETs is more accurate as compared to the LSTM model with accuracies of 92 and 90% for the training and validation datasets, respectively. The predictions made by the ensembled LSTM are more in line with the FAO-56 PM-based method with a Pearson correlation of 0.916 as compared to LSTM models. The implementation of the proposed solution in real-time environments reveals that the proposed solution is more effective in reducing the soil salinity as compared to the traditional method.

INDEX TERMS Evapotranspiration (ET), evapotranspiration for saline soils (ETs), saline soil, long short-term memory model (LSTM), ensembled LSTM, FAO-56 Penman-Monteith, leaching process.

I. INTRODUCTION

Evapotranspiration (ET) is an important part of any hydrological cycle [1]. ET is the basis of precision agriculture to support efficient irrigation water for the conservation of irrigation water [2]. The application of extra irrigation water to leach down the salts from the root zone of the plants is practiced in many parts of the world to deal with the issue of human-induced soil salinity [3]. The leaching process usually fails to achieve its objectives, resulting in a huge loss to farmers. For an effective leaching process, the irrigation water needs to be applied according to context-aware Evapotranspiration for saline soils (ETs). The irrigation water in saline soil is not applied according to ET due to the complexity associated with the standard ET method in general and especially for saline soil.

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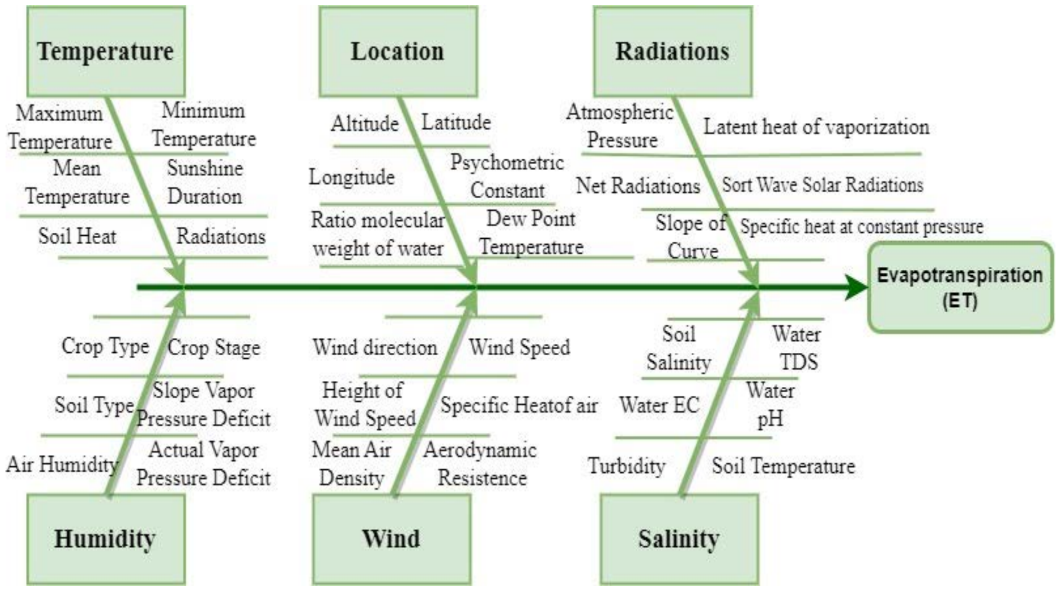

FIGURE 1. Factors affecting evapotranspiration (ET).

The application of ET for saline soil reclamation is very important for the effective leaching process. Effective leaching process with conservation of irrigation water for saline soils is challenging due to the involvement of many parameters associated with the determination of ETs as shown in Fig. 1.

Soil salinity is a soil degradation process due to the accumulation of high concentrations of salt in soils [4]. Soil salinity is an environmental hazard for sustainable developments in agriculture [5]. Soil salinity is present in more than one hundred countries. The increasing sea levels due to global climate changes, it is increasing at an alarming rate. Soil salinity is a serious hazard that is associated with the destruction of human civilization for centuries like Mesopotamia civilization [6]. Soil salinity is the major threat to productivity in agriculture [7]. Soil salinity results in a reduction in the quantity and quality of agricultural items [8]. The major threat of soil salinity is the loss of precious land resources that become unfit for agricultural purposes [9]. The soil salinity distribution in the experiment area is shown in Fig. 2.

Soil salinity is the major issue in arid and semi-arid regions with low rainfall and high temperature. The evaporation of water leaves behind salt in soils. The low rainfall results in poor leaching of salt in these areas. Poor agronomic activities like imbalance use of fertilizers and poor irrigation water quality are the major reasons for secondary or human-induced soil salinity. To deal with the issue of soil salinity, many solutions were in practice including the leaching of the salt into the lower layer for reclamation of soil salinity. For an effective leaching process, the precise use of irrigation water is important, but it is usually not followed. The failure of the leaching process results in huge losses to farmers. Moreover, irrigation water is a scarce resource that needs to be used efficiently to support sustainable development in agriculture.

FIGURE 2. Salt affected soil in the experiment area.

For an effective leaching process, the irrigation water needs to be applied according to the crop field context-aware ETs. The determination of ETs by a standard method like the Penman-Monteith method is very complex. The optimal use of irrigation water is the foundation of sustainable developments in agriculture. Predicting the ET variations is important for efficient irrigation water management. In saline soils, accurate estimation of ETs is even more important for an effective leaching process. Irrigation water is a scarce resource that needs to be applied by the standard Penman-Monteith recommended method. The precision irrigation water needs to be applied according to ET for efficient irrigation water with conservation of irrigation water. The dearth of fresh irrigation water provokes the urgency of the efficient use of irrigation water for the conservation of irrigation water resources [10].

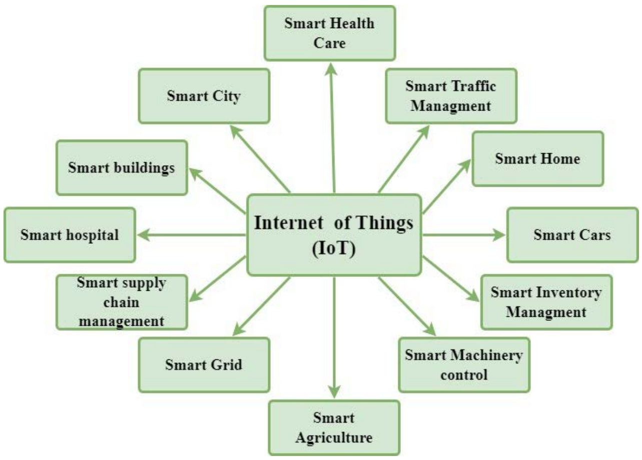

FIGURE 3. **Internet of things (IoT) applications in agriculture.**

Internet of Things (IoT) is a paradigm that can effectively be used to capture the context to adjust the services. IoT is being successfully used in different areas like smart homes, smart traffic, smart cities, and precision agriculture [11]. IoT applications in different fields are shown in Fig. 3.

IoT has revolutionized the world by enabling customized services according to the context. IoT applications in agriculture can transform the traditional cultivation process agriculture. IoT has great prospects to deal with long-lasting problems in agriculture. IoT is the most promising technology for precision agriculture applications. IoT is also important for ETs determination according to the crop field environmental context. The IoT-enabled context will be useful for accurate ETs prediction.

Moreover, the theory of Machine learning also got revolutionary prospects in precision agriculture to support sustainable development [12], [13]. The combination of IoT and machine learning are very useful in agriculture to deal with different issues in agriculture [14]. This combination is quite effective to improve the quality and quantity of products with the conservation of resources to meet the needs of the ever-increasing human population [15], [16]. Machine learning and IoTs have great potential for smart agriculture applications [17]. For effective ETs for saline soils, IoT and machine learning are strong candidates to effectively deal with the issue [18]. IoT provides the precise environmental and soil context in terms of the level of soil salinity and environmental conditions to accurately predict the ETs according to the prevailing contextual information. Machine learning is useful for the determination of the ET for saline soils using machine learning with limited input parameters.

The study proposes IoT and machine learning-based architecture of context-aware ETs estimations for saline soil reclamation with the effect leaching process. The proposed solution is based on IoT-enabled directly sensed crop fields' environmental conditions and the salinity levels of soil and irrigation water. The crop field directly sensed context is fed into the machine learning model to determine the ETs for the reclamation of saline soils with limited available parameters. The unique contribution of the proposed solution is that ETs prediction is based on directly sensed crop field conditions to accurately predict the prevailing ETs.

A. CONTRIBUTION OF THE STUDY

The main contributions and novelties of the study are summarized as follows:

1. The study proposed smart ETs for the reclamation of saline soils that were not previously targeted in terms of an effective leaching process.
2. We have proposed the architecture of IoT-enabled context-aware smart ETs for accurate ETs predictions according to the prevailing crop field context.
3. The ETs are computed with the help of the proposed methodology by using limited meteorological conditions with the help of a machine learning approach.
4. A comparison is performed between the LSTM and ensemble LSTM models in terms of predicting the monthly ETs
5. The proposed solution is in line with the FAO-56 PM standard method. Moreover, to show the effectiveness of the proposed methodology, the proposed methodology is implemented practically in a real environment.

B. ORGANIZATION OF THE STUDY

The rest of the paper is organized as follows: Section II contains the literature review to explore recent advancements in smart and precision agriculture along with the prediction of ET rate with limited environmental conditions using modern machine learning approaches. Section III describes the proposed architecture along with the sensors used for the configuration of machine learning models and the dataset. The result and discussion section explore the accuracy of machine learning models along with the accuracy of ETs predictions with the help of the proposed methodology. The results are discussed, and conclusions are drawn in Sections V and VI, respectively.

II. LITERATURE REVIEW

IoT and machine learning are extensively used for agriculture applications. Many exciting solutions are proposed using modern sensors and IoT technologies to deal with low productivity in agriculture. IoT is used for monitoring and context of the services. Machine learning is extensively used to determine the irrigation water requirements in the form of ET with minimal available parameters. In this section, the recent emerging solutions of smart and precision agriculture applications and machine learning-assisted ET proposed solutions are reviewed. Major bibliography indices are searched to review the existing solutions.

Bwambale [19] review the smart irrigation water strategies using the IoT for irrigation water scheduling. The study explores soil, plant, and environment-based monitoring and irrigation water scheduling with the conclusion that smart irrigation is effective for the conservation of irrigation water. Akhter and Sofi [15] explore the challenges and effects of the applications of data analytics, machine learning, and IoT in agriculture. Sengupta *et al.* [20] propose a quadcopter based IoT system named "FormFox" to monitor plant health systems in terms of pH and turbidity.

Ponnusamy and Natarajan [21] explore the potential of IoT, augmented reality, and machine learning in agriculture. Garg *et al.* [22] propose IoT-based soil moisture and nutrients monitoring for irrigation water and fertilizer recommendation with a pre-trained Convolution Neural Network (CNN). Sirisha and Sahitya [23] propose ET prediction with IoT-assisted soil moisture monitoring with help of Kernel Canonical Correlation Analysis (KCCA) by using the Support Vector Machine (SVM) with kernel function for smart irrigation water scheduling. Pincheira *et al.* [24] propose energy-efficient IoT and blockchain-based smart irrigation water scheduling. Alfred *et al.* [17] propose an IoT framework for smart paddy rice crops with the purpose of smart irrigation, yield estimation, and paddy rice growth monitoring.

Boursianis *et al.* [25] propose an IoT architecture named ARETHOU5A-IoT for intelligent irrigation systems with IoT node operations and radiofrequency harvesting techniques for IoT platforms in agriculture. Keswan *et al.* [26] propose an IoT framework for monitoring soil moisture, soil temperature, humidity, air temperature, daylight, and CO_2 for the estimation of irrigation water requirements by the neural network model.

Torky *et al.* [27] review the emerging IoT and blockchain technologies in smart applications for precision agriculture. Yin *et al.* [28] explore the potential of different types of soil sensors with the challenges associated with their applications in precision agriculture. Babaeian *et al.* [2] propose long short- and medium-term ET forecasts to analyze the impacts of climatic changes on energy and water balance and to forecast the real-time demand of actual Evapotranspiration (ETa). The proposed solution uses the Long Short-Term Memory (LSTM) and Convolution LSTM (Conv-LSTM) model to forecast the ETa from remote sensing data for different climatic zones of the United States of America (USA).

Bispo *et al.* [29] proposed remote sensing based on ETa for the sugarcane crop with help of Remote Sensing Water Balance (RSWB) and Two Source Energy Balance (TSEB) models. The Pearson correlation coefficient for the ET between the proposed solution and ground data for ET is 0.88. Aghelpour and Norooz [1] propose daily ET estimation by stochastic machine learning models in the Mazandaran province in Iran. The study compares the performance of stochastic methods and different machine learning models like Least Square Support Vector Machine (LSSSVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Generalized Regression Neural Network (GRNN) to forecast daily ET. The result of the proposed solution reveals that stochastic methods are more accurate as compared to machine learning in daily ET forecasts. The Autoregressive Moving Average (ARMA) model shows high accuracy with Root Mean Squared Error (RMSE)0.623 mm day^{-1} and 86.22 % of the coefficient of determination R^2 in daily ET prediction. Elgeltagi *et al.* [30] assess the ET models in the Nile delta in Egyptian regions. The proposed solution is based on monthly maximum and minimum temperature data for ET calculation. The green water ET and blue water ET are determined with 099 and 0.76 coefficient of determination (R^2).

Dimitriadou and Nikolakopoulos [31] evaluate the performance of the Artificial Neural Network (ANN) for the Peloponnese Peninsula in Greece. The dataset comprising of mean temperature (Tmean), sunshine (N), solar radiation (Rs), net radiation (Rn), vapor pressure deficit (es-ea), wind speed (u2), and altitude (Z) from the year 2016 to 2019 for sixty-two weather stations. The performances of nineteen Multi-layer Perceptron (MLP) and Radial Basis Function (RBF) models are compared against the FAO-56 PM method. The results reveal that the MLP1 7-2 model with all the variables as inputs outperformed the rest of the models (RMSE = 0.290 mm d−1, R2 = 98%).

El-Kenawy *et al.* [32] evaluate the performance of the hybrid ensemble model in the prediction of daily ET. Srivivosa Peddinti *et al.* [33] assess the impacts of salinity on soil moisture by using sensors for precision agriculture applications. Ramchandran *et al.* [34] propose automated irrigation water solutions using IoT, and cloud computing to conserve irrigation water. Gentilucci *et al.* [35] determine the ET using temperature data only, and ET0 is calculated with the Hargreaves–Samani (HS) formula by using the Hargreaves coefficient.

Kisi *et al.* [36] compare the performance of different machine learning and deep learning models in the determination of pan-evaporation. The results reveal that LSTM with grey wolf optimizer outperforms other models in the determination of Epan. Balducci *et al.* [37] propose a smart farm framework from harvest forecasting to sensory data reconstruction. The study proposes a machine learning approach for the establishment of directions for smart farm developments.

Liao *et al.* [38] propose nocturnal evapotranspiration (ETN) estimation of Qinghai Lake Basin in alpine regions to observe the ET variations during the day and nighttime. Masseroni *et al.* [39] in a special issue explore different approaches to the smart irrigation water system for sustainable agriculture. Niaghi *et al.* [40] compare the machine learning approaches with seventeen-year data from six weather stations in the red river valley. Campos *et al.* [41] propose a smart irrigation system with IoT by sensing soil moisture. The framework includes monitoring, preprocessing, fusion, synchronization, storage, and irrigation management. Salazar *et al.* [42] propose remote sensing-based ET predictions with MODIS ET data. Munir *et al.* [43] propose an intelligent IoT-based method for efficient irrigation of crop plants based on the level of soil moisture, humidity, crop type, and time.

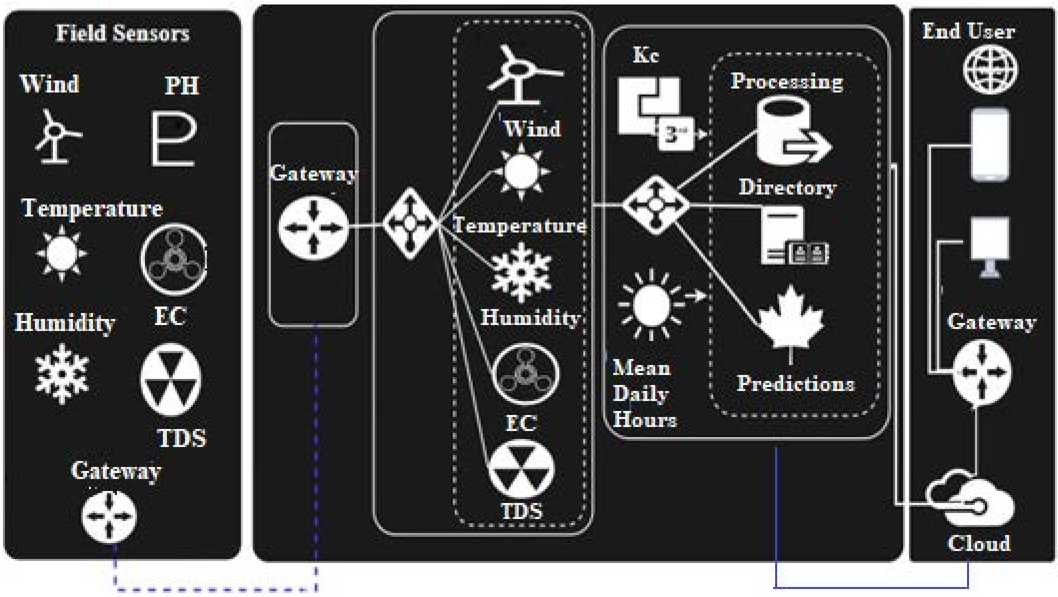

FIGURE 4. The architecture of the proposed solution.

Keshtegar *et al.* [44] propose regression modeling for daily ET for efficient irrigation water scheduling. The authors propose a hybrid approach for radial-based function and the M5 model tree. The proposed solution outperforms the response surface method (RSM), and neural networks (multi-layer perceptron neural networks, MLPNN & radial basis function neural network, RBFNN) for several statistical indices. Shafi *et al.* [45] propose crop health monitoring using IoT. Pan *et al.* [46] propose remote sensing and machine learning-based approaches for analyzing the variations in global terrestrial ET. Aggrwal and Kumar [47] propose IoT-based monitoring to determine irrigation water requirements using the ANN and automatic control of valves for irrigation water applications. Ahmadi *et al.* [48] explore the driving metrological forces in Et determinations using the Pearson correlation, mutual information, and random forest.

Many solutions were proposed using the IoT and machine learning approach with the purpose of smart irrigation water. Moreover, machine learning is widely used for ET determination with a limited dataset. However, the ET for saline soil is also important for an effective leaching process that was not previously targeted in the corpus of the existing research. Also, the IoT-based context-aware ETs are proposed to fill the gap and for the reclamation of saline soils.

III. MATERIALS AND METHODS

This section describes the proposed architecture, implementation of the proposed solution, the configuration of the machine learning model, sensors and the used prototypes used, the dataset, and the salinity mapping model.

A. ARCHITECTURE OF THE PROPOSED SOLUTION

The proposed solution of Evapotranspiration for Saline Soil (ETs) predictions is based on sensing crop field air temperature, soil salinity in terms of Electric Conductivity (EC), and irrigation water quality in terms of Total Dissolved Salts (TDS) and pH. The ETs are predicted by using a machine learning model. The architecture of the proposed solution is shown in Fig. 4. The sensed data from the crop field is transferred to the server through the cloud. The data at the server is converted into mean monthly environment conditions for monthly ETs predictions. The server processes the data using the machine learning model. The information from the server is accessed by the end user with Internet access.

FIGURE 5. Salinity mapping sensors A) MEC-10 Soil EC sensor B) TDS sensor C) pH sensor.

B. IMPLEMENTATION OF THE PROPOSED SOLUTION

1) SENSOR AND PROTOTYPE

For soil salinity, the Mec-10 soil EC sensor is used with the ability to observe the temperature of the sample. The irrigation water salinity is observed with TDS and pH sensors shown in Fig. 5.

FIGURE 6. Environment monitoring node.

FIGURE 7. Soil and Irrigation water salinity monitoring node.

To sense different environmental conditions of crop fields, the IoT prototype is used and implemented in the soil salinity-affected areas of Pakistan. The existing levels of soil salinity, irrigation water salinity, and air temperature are captured from the field with help of the prototype shown in Fig. 6 and Fig. 7.

2) CONFIGURATION OF MACHINE LEARNING MODEL

A machine learning model is used to define a function to determine the ETs from the intended features set expressed by Eq. 1.

$$F(X) \rightarrow ETs \tag{1}$$

where X is the input feature matrix comprised of input feature vectors 'x_i' for the month 'm' expressed by Eq. 2.

$$X = \{x_{m_1}, x_{m_2}, \ldots x_{m_n}\} \tag{2}$$

Each input vector x_{mi} is based on mean monthly temperature (Tmean), average soil salinity (SS_{avg}), and irrigation water salinity (SW). Each input vector 'i' comprised of the year (Y), month (m), Tmean for the month 'm', SS for the month 'm', and irrigation water salinity (SW) expressed by Eq. 3.

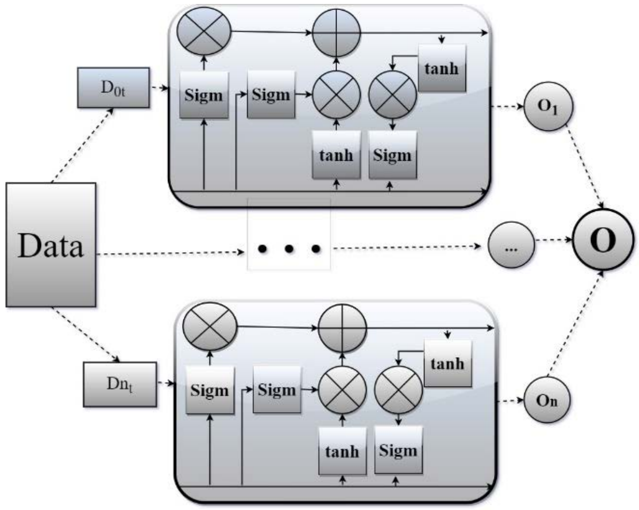

FIGURE 8. The architecture of ensembled LSTM.

$$X_{m_i} = \left\{Y_i, m_i, Tmean_{m_i}, SS_{m_i}, SW_i\right\} \tag{3}$$

The objective of the machine learning model is to minimize the difference between the ETs predicted by the model against the actual ETs by the FAO-56 PM method. The study intends to use the Long Short-Term Memory Model (LSTM) and ensembled LSTM model for ETs.

Long Short-Term Memory Model is the extension of the Recurrent Neural Network (RNN) to overcome the deficiency of short-term memory in the RNN model. LSTM is capable of learning long terms trends using memory cells and associated logic functions. The study also applies the ensembled LSTM model to improve the accuracy of ETs. The architecture of the proposed ensemble LSTM model is shown in Fig. 8. The ensembled LSTM model is based on a bagged ensembled approach with two LSTM models. The study also aims to compare the performance of the ensembled LSTM model against the individual LSTM model for ETs predictions with the intended data.

The models in the ensembled approach are ensembled by Algorithm 1, input feature set X, output ETs, and the number of models is the inputs, and the ensembled function is the output of the model.

The ETs are predicted by the ensembled LSTM with the combination of multiple models with Ø the weights of different models in ensembled LSTM models. The predicted $\widehat{ET}s$ from the ensembled model is expressed by Eq. 4.

$$\widehat{ET}_s = \emptyset \sum_{i=1}^{N} F_i(X_i, ETs_i) \tag{4}$$

The algorithm for $\widehat{ET}s$ predictions by ensembled LSTM models are made by algorithm 2. The weights of the models, ensembled models, and set of environmental conditions of the month are inputs to the model. The prediction of ETs for the

Algorithm 1

1. **Input:** X, ETs, N
2. **Initialize:** n ←1
3. **while** (n <= N) **do**
4. (X_n, ← ETs_n) F (X, ETs) // Use random replacement function to create (X_n, ETs_n) the subset of (X, ET_s)
5. $F_n(X_{n)} \rightarrow ETs_n$// training of the 'n' model in ensembled models
6. n←n+1
7. **End while**
8. **Output**: $F_1(X_{1)} \rightarrow ETs_1, F_2(X_{2)} \rightarrow ETs_2 \ldots F_n(X_{n)} \rightarrow ETs_n$

Algorithm 2

1. **Input:** $\emptyset, x_m, F_1(X_{1)} \rightarrow ETs_1, F_2(X_{2)} \rightarrow ETs_2 \ldots F_n(X_{n)} \rightarrow ETs_n$
2. **Initialize:** $\hat{y}_m \leftarrow 0$, n ← 2
3. **while** n≤ N **do**
4. $\widehat{ETs}_{m+1} \leftarrow \widehat{ETs}_m + \emptyset \sum_{i=1}^{N} F_i(x_m, ETs_i)$
5. n=n+1
6. **End while**
7. **Output**: $\hat{y}_{t+1}$

TABLE 1. Configuration of machine learning models.

PARAMETER	LSTM	ENSEMBLED LSTM
Epochs	100	100
Optimizer	Adam	Adam
Hidden layers	2	2
Nodes at the Input layer	4	4
Nodes at hidden layer 1	6	6
Nodes at hidden layer 2	6	6
Nodes at the output layer	1	1
Activation Function at all the input and hidden layers	ReLu	ReLu
Activation functions at output layers	Sigmoid	Sigmoid

month 'm' is made based on the same month from previous years.

The ensemble LSTM model is based on two LSTM models ensembled in a bagged manner. The configuration of both LSTM models in the ensemble approach is the same; therefore, the description of the ensembled model is similar for both LSTM models in the ensembled approach. The best performance is achieved with a maximum of 100 epochs for both LSTM and the ensembled LSTM model. Other configurations with the best performance for both LSTM and ensembled LSTM are given in Table 1.

3) DATASET

The proposed solution is implemented in Pakistan. Pakistan is situated in the South Asia continent. Pakistan is an agricultural country with arid and semi-arid climatic conditions.

FIGURE 9. The geographical location of Pakistan.

The high temperature and low rainfall in agriculture-intensive areas are favorable for the development of salinity hazards. Furthermore, the use of low-quality irrigation water is also a major reason for the development of salinity hazards. The geographical location of Pakistan in the world is shown in Fig. 9. The environmental dataset from the year 2011 to 2020 is collected for the Pakistan region.

The dataset for the model training is collected from NASA [49]. The environmental dataset is used to determine the prevailing ET and ETs by the FAO-56 Penman-Monteith method (FAO-56 PM). The irrigation water requirements of saline soil are determined based on Evapotranspiration (ET), prevailing soil salinity, and level of irrigation water salinity and expressed by Eq. 5.

$$ETs = \frac{ET}{1 - LF} \tag{5}$$

where LF is the leaching fraction, and ET is the Evapotranspiration rate. The Leaching Fraction (LF) of the irrigation water is the fraction of total irrigation water that would be used for the leaching process. The LF of irrigation water is determined based on existing soil salinity (ECe) and irrigation water salinity ECw expressed by Eq. 6.

$$LF = \frac{ECw}{5\,(ECe) - ECw} \tag{6}$$

The ET for Eq. 5 is determined by the FAO-56 PM method. The FAO-56 PM is the Food and Agriculture Organization (FAO) recommended standard method of ET determination according to the prevailing environmental conditions. The FAO-56 PM method for ET is expressed in Eq. 7.

$$ET_0 = \frac{0.408\Delta\,(Rn - G) + \gamma \frac{900}{T+273}(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{7}$$

where ET_0 is reference evapotranspiration in mm per day, R_n is the net radiation in megajoules per square meter per day (MJ m^{-2} day^{-1})·G is the soil heat flux density in megajoules per square meter per day (MJ m^{-2} day^{-1}), T is the air temperature in degree centigrade (°C), U_2 is the windspeed in miles per second, e_s is the saturated vapor pressure in kilopascals (kPa), e_a is the actual vapor pressure in kilopascals (kPa), e_s-e_a is the saturated vapor pressure deficit in kilopascals (kPa), Δ is the slope vapor pressure curve in kilopascals (kPa) per degree centigrade (°C), and γ is the psychrometric constant kPa per degree centigrade (°C).

C. SALINITY MAPPING MODEL

Soil and irrigation water salinity is observed in terms of the Electric Conductivity (EC) model [50]. The EC model of salinity enables the use of sensing technology for direct sensing of soil salinity. The EC model measures the salinity in terms of the total concentration of salt. The salt in water and soil solution enables the passage of current that is measured in terms of EC. The ability to conduct electricity is used as a measure of the concentration of salt. The EC unit is desi-Siemens per meter (dSm^{-1}). Salinity in terms of EC observed at different temperatures is standardized at 25 °C by Eq. 8.

$$EC_{25} = \frac{Observed\ EC\ \ value}{1 + (0.02 \times (Temperature(°\mathrm{C}) - 25)} \tag{8}$$

The salinity of the irrigation water is observed using the Total Dissolved Salts (TDS) sensor and PH sensor. TDS is the measure of total salts in water and PH is the measure of acidity and alkalinity of the irrigation water. The TDS value from the sensors is converted to the EC value by Eq. 9, where 'k' is the constant rate.

$$TDS = k\ EC\ at\ 25°\mathrm{C} \tag{9}$$

IV. RESULTS

The proposed solution is evaluated in terms of the accuracy of the machine learning model, and the accuracy of ETs prediction by the proposed solution as compared to the FAO-56 PM-based standard method and through field observations.

A. PERFORMANCE OF THE MACHINE LEARNING MODEL

The performance of the machine learning model is observed in terms of accuracy and loss by machine learning models.

1) ACCURACY OF THE MACHINE LEARNING MODEL

The accuracy is the fraction of correct ETs predictions to the total ETs predictions expressed by Eq. 10.

$$Accuracy = \frac{Correct\ ETs\ predictions}{Total\ ETs\ predictions} \tag{10}$$

The accuracy of LSTM from the training and validation data over 100 epochs is shown in Fig. 10. The maximum training and validation accuracy of LSTM is 0.90 and 0.87 respectively.

The accuracy of LSTM from the training and validation data over 100 epochs is shown in Fig. 11. The maximum accuracy of the ensembled LSTM model is 0.92 and 0.90 from the training and validation dataset. The accuracy of the ensembled LSTM model is high as compared to the LSTM model from both the training and validation dataset. The accuracy of both models is compared in Table 2.

2) LOSSES COMPARISON OF THE MACHINE LEARNING MODEL

Loss is the difference between the predicted ETs by the machine learning model as compared to the actual ETs value expressed by Eq. 11.

$$\mathrm{loss} = \mathrm{abs}\left(\widehat{ET}_{s_i} - \mathrm{ET}_{\mathrm{s_i}}\right) \tag{11}$$

The minimum loss from the LSTM is 0.28 and 0.30 with the training and validation dataset as shown in Fig. 12. The minimum loss from the ensembled LSTM is 0.21 and 0.22 with the training and validation dataset as shown in Fig. 13. The ensembled LSTM is more efficient in reducing the losses as compared to the LSTM model.

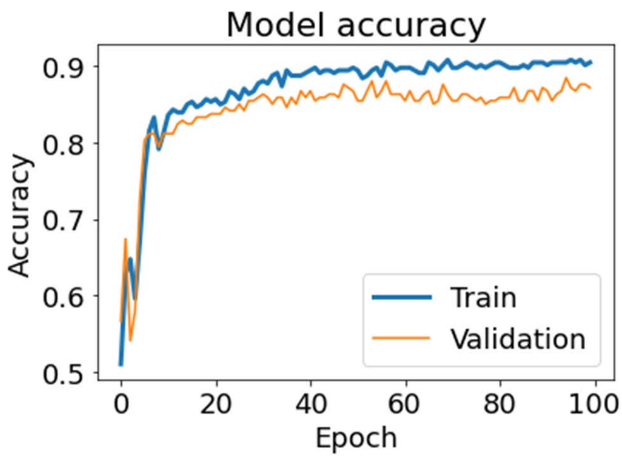

FIGURE 10. Training and validation accuracy of the LSTM model.

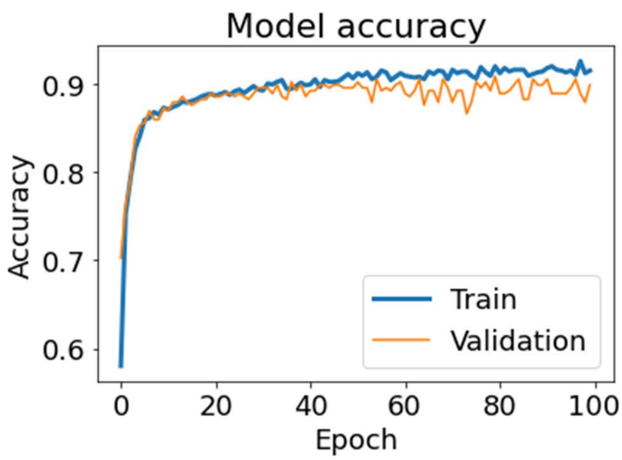

FIGURE 11. Training and validation accuracy of ensembled LSTM.

TABLE 2. Accuracy comparison of models.

Model	Training	Validations
LSTM	0.90	0.87
Ensemble LSTM	0.92	0.90

B. COMPARISON AGAINST THE FAO-56 PENMAN MONTIETH-BASED STANDARD METHOD

The performance of the proposed solution is also compared against the FAO-56 PM-based standard method. The ETs predictions by the proposed solutions are compared against

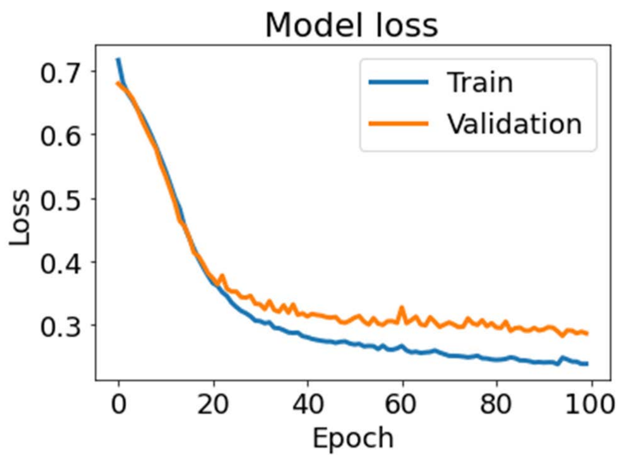

FIGURE 12. Training and validation losses of the LSTM model.

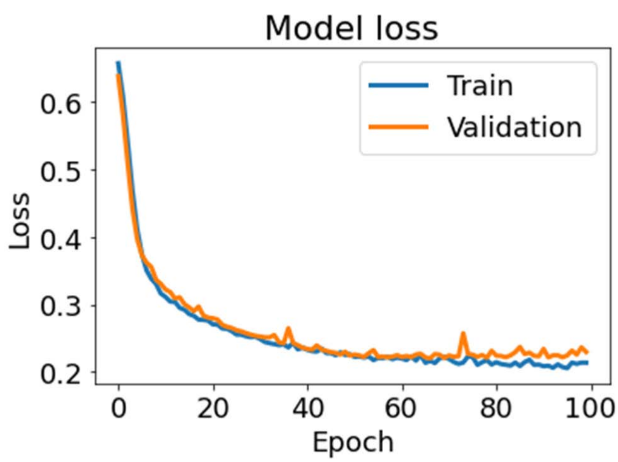

FIGURE 13. Training and validation loss of ensembled LSTM.

the FAO-56 PM-based standard methods to prove the accuracy and validity of the proposed solutions. The ETs by the FAO-56 PM-based standard method, ensembled LSTM, and LSTM are shown in Fig. 14. The ETs prediction distribution by the ensembled LSTM is more similar to the FAO-56 PM-based standard method. The difference in ETs by LSTM and ensembled LSTM against the standard method is shown in Fig. 15. The differences in ETs predictions against the FAO-56 PM-based standard method are low in the case of ensemble LSTM as compared to predictions by the LSTM model.

The correlation between the ETs predicted by the ensembled LSTM and the standard method is 0.916 as shown in Fig. 16. The correlation between the ETs predicted by the ensembled LSTM and the standard method is 0.916 shown in Fig. 17. The difference in ETs predictions by ensembled LSTM against the standard method is less as compared to the LSTM.

The difference in predictions of mean monthly ETs by LSTM and ensemble LSTM is shown in Fig. 18. The difference between ETs predictions by the ensemble LSTM

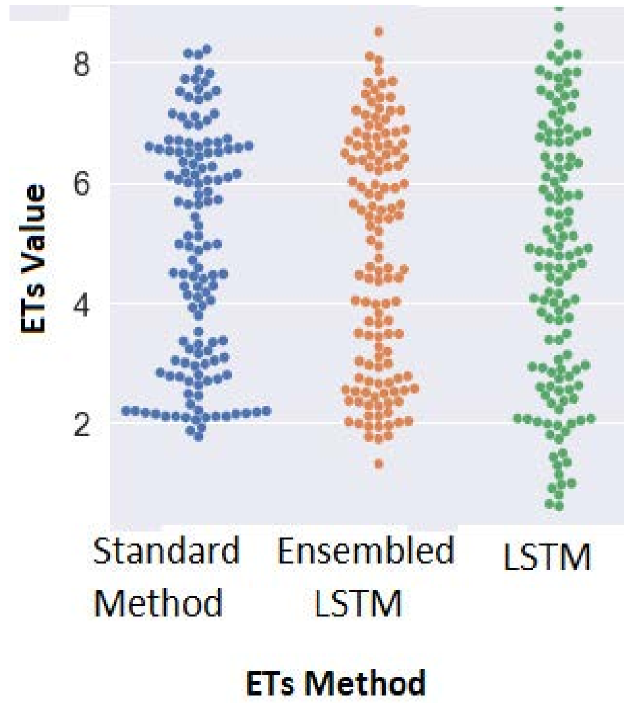

FIGURE 14. ETs predictions by different methods.

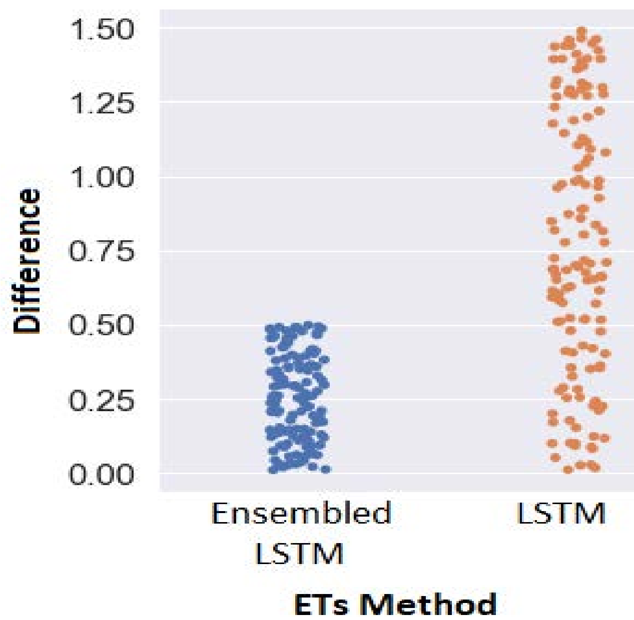

FIGURE 15. The difference in ETs prediction by LSTM and ensembled LSTM against the standard method.

against the FAO-56 PM method is lower as compared to the difference by LSTM. The predictions made by the ensembled model are more accurate and in line with the FAO-56 PM-based standard method.

C. REAL-TIME FIELD EVALUATIONS

The proposed solutions are also implemented in a real-time environment to observe the effectiveness of the proposed

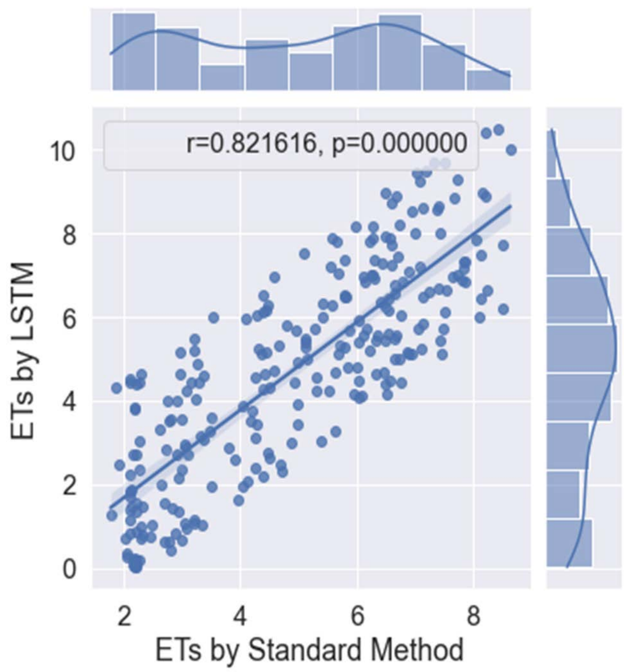

FIGURE 16. Correlation between ETs by LSTM and standard method.

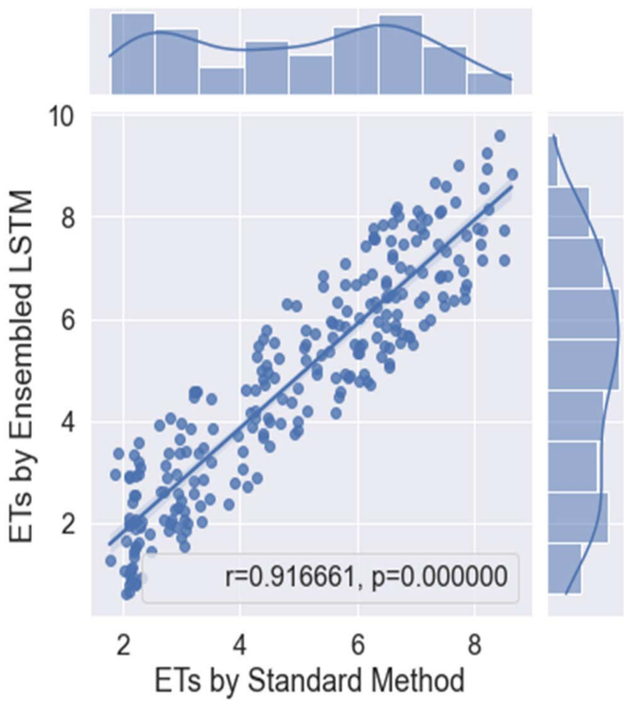

FIGURE 17. Correlation between ETs by ensembled-LSTM and standard method.

solutions as compared to the traditional method. For field evaluation, two adjacent areas of one acre each, with similar salinity distribution are selected. The salinity is observed before and after the application of irrigation water. In the control area, the irrigation water is applied according to the

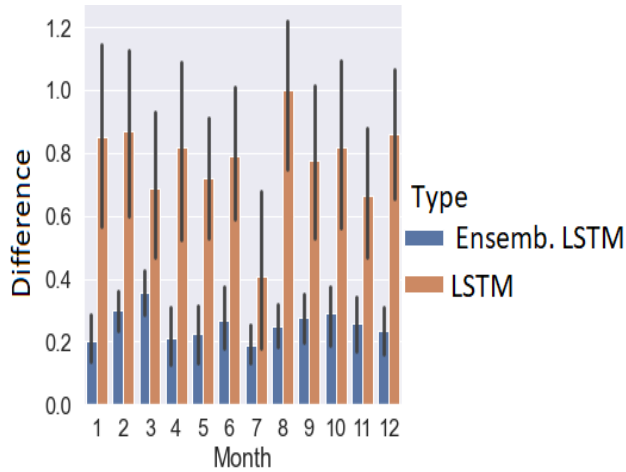

FIGURE 18. Difference of mean monthly ETs by LSTM and ensembled LSTM against the standard method.

TABLE 3. Comparison of loss.

Model	Training	Validations
LSTM	0.28	0.30
Ensemble LSTM	0.21	0.22

TABLE 4. Salinity in comparison to control and experiment.

Area	Training		Validations	
	Average EC	N>EC5	Average EC	N>EC5
Control Area	10.78	64	8.28	32
Experiment Area	11.01	64	6.95	14

traditional irrigation water application without considering the environmental and salinity context. In the experiment area, the irrigation water is applied according to the proposed solution. The effectiveness of the leaching process is observed in terms of average salinity and the number of sample points with salinity above the threshold value of 5 dSm^{-1}. The salinity distribution before and after the application of irrigation water by the proposed solution and by the traditional method is shown in Fig. 19.

The traditional method of irrigation water reduces average salinity in control areas from 10.78 dSm^{-1} to 8.28 dSm^{-1}. The proposed method in the experiment area reduces salinity from 11.01 to 6.95 dSm^{-1}. The proposed method of salinity is more effective in reducing the salinity at more sample points as compared to the traditional method. The effectiveness of both methods in reducing soil salinity is given in Table 4. The proposed smart ETs solution for saline is more effective in reducing the soil salinity in the experiment area as compared to the traditional area.

V. DISCUSSION

The proposed solution for ETs directly sensed crop field environmental conditions, and it is implemented using the proposed IoT and machine learning-based architecture. The

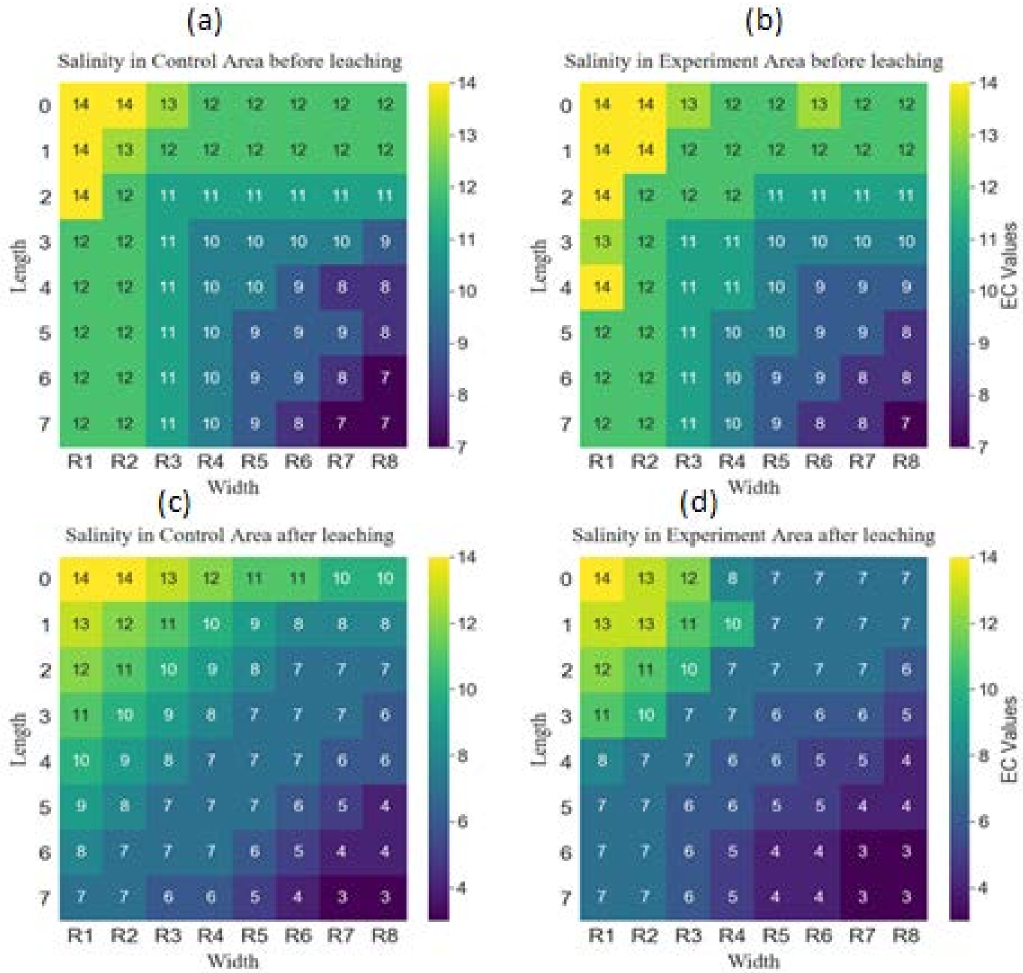

FIGURE 19. **Effectiveness of proposed solution in reducing salinity as compared to the traditional process a) Salinity distribution in control area before leaching process by traditional method b) Salinity distribution in experiment area before ETs application c) Salinity distribution in control area after leaching process by traditional method d) Salinity distribution in experiment area after ETs application.**

performance of the LSTM and ensembled LSTM model is also compared for ETs predictions. The performance of the ensemble LSTM model is better than the LSTM model in terms of accuracy and loss. The maximum accuracy of the ensembled LSTM model is 92 % as compared to 90% of the LSTM model from the training dataset. With the training dataset, the ensembled LSTM is 2.22% more accurate than the LSTM in terms of ETs predictions.

The maximum accuracy of the ensembled LSTM model is 90 % as compared to 87% of the LSTM model from the validation dataset. The ensembled LSTM is 3.4%% more accurate than the LSTM model in terms of predicting ETs from mean monthly temperature (Tmean), existing soil salinity, and the level of irrigation water salinity.

The Pearson Correlation between the ETs predictions by ensemble LSTM and FAO-56 PM based method is 0.91 as compared to 0.82 computed between the ETs predictions by LSTM and FAO-56 PM based standard method. The predictions by the ensemble LSTM model are more in line with the FAO-56 PM-based standard method as compared to the LSTM model.

The proposed solution is also implemented in real-time environments to observe the impacts of proposed solution recommendations on the leaching process. The results are compared against the traditional methods by observing the sail salinity at sixty-four sample points in each experiment and control area. The average salinity in the experiment area gets reduced from 11.01 dSm^{-1} to 6.95 dSm^{-1}, while the average salinity gets reduced from 10.78 dSm^{-1} to 8.28 dSm^{-1} in the control area. The proposed solution is more successful in reducing the soil salinity below the threshold level of 5 dSm^{-1} at 50 sample points in the experiment area. The salinity in the control area gets reduced at 32 sample points with the traditional method. Therefore, the proposed solution is more successful in reducing the soil salinity in terms of average salinity and threshold level of salinity at different sample points.

VI. CONCLUSION

The study proposed Evapotranspiration for saline soils (ETs) as an effective leaching process to reclaim saline soil. Internet of Things (IoT) based crop field environmental and salinity context is used to determine ETs with machine learning models. The mean monthly temperature (Tmean), Year, Month, the existing level of soil salinity, and salinity of irrigation water are used as input features to the machine learning model. The Long Short Term Memory Model (LSTM) and ensembled LSTM model are used to predict the monthly ETs for the effective leaching process in saline soils. The ensembled LSTM model is more accurate in the prediction of ETs from training and validation datasets with accuracies of 92 and 90%, respectively. The ETs predictions by the ensemble LSTM are more in line with the standard approach as compared to the LSTM model with a 0.916 Pearson correlation. The implementation of the proposed solution in the experiment areas reveals that the proposed solution is more effective in reducing soil salinity as compared to the traditional method.

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