

PREDICTION OF GLOBAL WARMING ON CROP YIELD INTEGRATING EDGE COMPUTING AND KALMAN RICCATI SUPPORT VECTOR REGRESSION

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ABSTRACT:

Agricultural production to a large extent depends on weather conditions. The caution of global climate change or global warming has extensively caught the curiosity of researchers as these changes are reporting negative influences on overall crop production. Edge computing in the period of digital evolution, is steadily receiving drive across several industries. In spite of cloud configuration has hitherto played a paramount role in boosting the agricultural sector, edge computing outperforms in terms of both speed and efficiency. While exploiting edge computing technique farmers rely on data to acquire enhanced control over the industry and optimize the effectiveness of their functioning that in turn results in minimized operational expenses too. Edge computing and machine learning can be employed cooperatively in agriculture to enhance data processing and decision-making. In this work an edge computing model is integrated with machine learning technique for analyzing the impact of global warming on agriculture for enhancing crop yield prediction both accurately and in a computationally efficient manner. The method is called, Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) based Crop yield prediction. With the overall method being split into three layers, the first layer collects the data and is sent to the second layer. The second layer or the edge device performs the pre-processing and feature extraction by employing Kalman Bucy Riccati Filter-based preprocessing and Spatial Temporal Regression based Feature Extraction. With this the edge device sends processed, relevant and valuable data to third layer. The third layer or the cloud server with the aid of Support Vector Regression function performs the classification with minimal error, therefore producing accurate and precise prediction results. Extensive simulation is done using Edge Cloud Simulator and Python programming language and detailed comparison is made with the state-of-the-art work in terms of prediction accuracy, precision, recall, prediction time and prediction error.

Keywords: *Edge Computing, Cloud Server, Kalman Bucy Riccati, Spatio-Temporal Regression, Support Vector.*

INTRODUCTION

Agriculture and climatic conditions are inmost associated with each other in different facets as climate change is the paramount characteristic of plant biotic and abiotic stresses, that have an unfavorable impact on global agriculture production. Some of them to name are, discrepancies in annual rainfall, temperature changes, heave waves, change in ozone level, global atmospheric CO₂, and so on. Edge computing can assist agriculture become more imperishable and minimizes its environmental influence in different facets.

Edge Computing with auction and Fuzzy Neural Network (EC-aFNN) was proposed in [1] that hid actual bid values and also regulated flow of information, followed by which machine learning techniques were applied for performing robust predictive analytics. Initially, rule-based fuzzy systems performing the encoding part to ensure domain expertise in agricultural decisionmaking. Next, adaptable training algorithms were applied to assist in optimizing model parameters from data. To achieve these two objectives, a two-phase hybrid learning method was applied, where fuzzy optimization models were performed exploiting three key supply chain decision problems. Next, fuzzy systems were employed in incorporating domain knowledge into interpretable crop-advisory models ensuring high performance with minimal error. Despite improvement observed with minimal error, however the accuracy rate involved was not analyzed.

Yet another hybrid method called, Multi Layer Perceptron Sperm Swarm Optimization (MLP-SSO) was proposed in [2] for both forecasting soil temperature and imparting them to tackle data driven discernments for managing resource in an optimal manner and supportable agricultural practices. Initially, Multi-Layer perceptron (MLP) was applied for forecasting soil temperature at various depths and then, a sperm swarm optimization (SSO) model was applied that in turn explored the entire search space with the objective of exploring and obtaining optimal solution with minimal forecast error. Though minimal forecast error was ensured, however the prediction time was not focused.

1.1 Research contributions

Motivated by the above issues, like, precision, recall, accuracy, prediction error rate and prediction time for analyzing the impact of global warming on agriculture crop yield prediction, in this work, a Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) is designed using Kalman Bucy Riccati and Spatio-Temporal Regression based Feature Extraction and Support Vector Regression based classification. The major contributions of this work are pointed below.

- To present a significant method for analyzing the impact of global warming on agriculture crop yield prediction, recommendation model called, Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR).
- To design outlier eliminated processed results, Kalman Bucy Riccati Filter-based pre-processing is applied to the raw training and testing dataset.
- To propose a machine learning model called Spatial and Temporal Regression model for extracting spatial and temporal features separately, therefore reducing the prediction error and prediction time correspondingly.
- To improve precision, recall and accuracy using Support Vector Regression Fitness for improved classification results.
- Finally, performance of the proposed KRST-SVR method based crop yield prediction is compared with the traditional state-of-the-art methods.

1.2 Article organization

For a thorough understanding of the literature, Section 2 looks closely focuses at the theories and related research about climate change and its influence on agriculture using machine learning and deep learning techniques. Section 3 describes the dataset description, technological perspective, separately for preprocessing, feature extraction and classification for accurate crop yield prediction. Section 4 describes the experimental setup followed by the method performance of various methods in Section 5. Finally, section 6 concludes the entire work.

RELATED WORKS

One of the major forces that influence agricultural production is weather and climate change has moreover raised issues about its influence on crop yields globally. Machine learning framework was applied in [3] to measure the influence of climate change on two different crops, maize and soybean. Over the past few years, the area of artificial intelligence (AI) has made an appearance as a prospective tool potential of instituting an intense impact on the agriculture production. With the objective of ensuring sustainable agriculture the application of AI was investigated in [4]. Several previous reports have confirmed that climate change unevenly influences farmers as far as developing countries are concerned. An in-depth investigation of the influence of climate change application along with the detailing of farmers decisions in applying enhanced methods to minimize influence of climate change was presented in [5]. Yet another plethora of techniques were analyzed in [6] with the applications of AI in agriculture.

To implement precise agriculture practices, one of the major requirements is the delineation of agricultural parcels in an accurate manner. Nevertheless one of the chief issues revolves around the parcel edges extraction in an accurate fashion. A refined edge-aware convolutional neural network was designed in [7] to address on this aspect with improved accuracy. Yet another method for smart irrigation system employing IoT and edge computing was presented in [8] with improved throughput and response time. An investigation of sustainable agriculture towards reliability was presented in [9]. A survey of smart agriculture mechanisms employing machine learning was investigated in [10].

Smart agriculture and edge computing were analyzed for improved crop yield prediction in [11]. AI applications were explored in [12] for ensuring sustainable AI-based production in an extensive manner. A comprehensive

review of evaluating machine learning techniques for precision farming in agriculture was investigated in [13]. Climatic conditional change paramount influences production of agriculture globally giving room for several uncertainties. To explore these climatic changes, a review of climate change influence on crop yield was presented in [14]. Yet another comprehensive review of global climate change on agricultural production was investigated in [15]. An in-depth assessment of ML techniques for risk factors involving climatic aspect concerning agriculture was designed in [16].

With the ceaseless evolution of agricultural Internet of Things (IoT) techniques, monitoring of agricultural environments in a real time fashion has become progressively paramount. This monitoring in turn ensures valuable information on subsequent ecological condition. Research on application of edge computing and deep learning towards agricultural environment monitoring was investigated in [17]. Yet another method combining support vector machine and cellular automata was designed in [18] with improved prediction accuracy. However with limited training samples the prediction accuracy was said to be compromised. To address on this aspect, a refined edge-aware CNN was presented in [19] with both improved accuracy and minimal training time.

An integrated regression model was introduced in [20] for crop yield prediction with improved accuracy and minimal training time. However the prediction error rate was not analyzed. To address on this issue, a crop yield prediction algorithm employing decision tree was presented in [21] that in turn not only improved accuracy rate involved in prediction but also reduced the error rate considerably. Yet another hybrid method combining Deep CNN and long short term memory was designed in [22] to focus on the error aspect involved in yield prediction. A plethora of climate change aspect influencing smart agriculture was investigated in [23]. ML and IOT was integrated in [24] with the intent of focusing on the crop yield prediction aspects. ML technique for analyzing influence of climatic change on agriculture production was investigated in [25].

In spite of the fact that machine learning methods have been paramount employed in the domain of agriculture crop yield prediction however the influence of global warming on agriculture has received greater attention among the researchers due to high climatic changes. As discussed earlier, we will demonstrate that machine learning technique to ensure accurate and precise crop yield with influence of global warming on agriculture employing Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) method with minimal time and error will be investigated in the next section.

METHODOLOGY

Upon comparison to other industries agriculture sector is considered as one of the world's critical industries and has conventionally been deliberate to strengthen and apply sophisticated techniques than other industries. As of now evolutions are materializing as digitization is becoming more feasible. Agricultural sector is discerning the advantages of sophisticated techniques, like machine learning (ML), process automation, edge computing and so on. Edge computing is applied by several industries encompassing the agricultural industry. Edge computing is one of the progressing techniques that have the prospective to bring evolution in the agricultural sector. In proposed methods, sensors are attached with the objects for acquiring corresponding data, e.g. average temperature, total precipitation, total emission of CO₂, total crop yield, and so on in case of agricultural productivity prediction. The collected data is sent to the associated edge device that does the task of data pre-processing. The pre-processed data is then sent to the cloud servers for storage and further analysis. Figure 1 shows the proposed method.

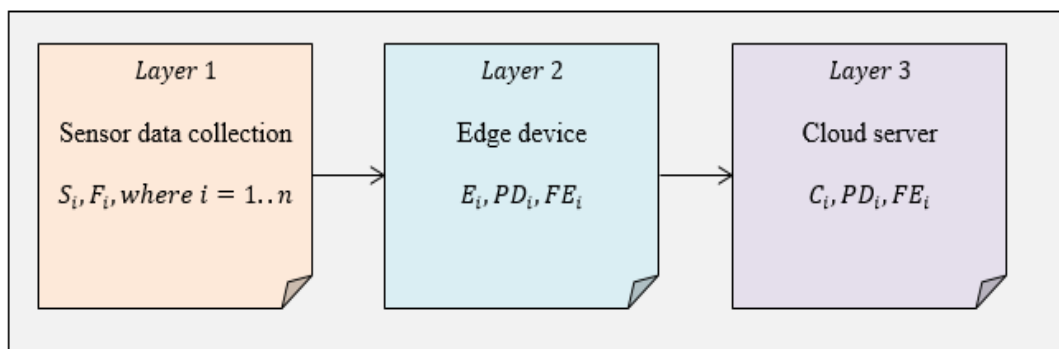


Figure 1 Structure of proposed method.

As illustrated in the above figure the overall process of the proposed method is split into three layers. Layer 1 consists of the sensors attached with the respective objects or features (i.e. 15 features from our dataset). The sensor node is denoted in the form of a three tuples $S = (S_i, F_i, S_{stat})$, where S_i presents the ID of the sensor (i.e. year of the climate change being analyzed), F_i presents the feature with which it is associated and S_{stat} presents the sensor status of sensor (i.e. active or inactive). In layer 1 the sensors acquire the object or feature status and send the data to layer 2.

Layer 2 contains edge device. The edge device is denoted in the form of a two tuples $E_{in} = (E_i, E_{stat})$, where E_i presents the ID of the edge device and E_{stat} presents the edge status (i.e. active or inactive). The edge device acquires data from sensors present at layer 1, then pre-processes the received data and performs feature extraction. Followed by pre-processing and feature extraction, the edge device sends processed and relevant and valuable data to layer 3.

After pre-processing and extracting relevant, valuable features, the edge device sends the data to layer 3. Layer 3 contains cloud servers. The cloud computing layer is represented as a three tuple $C = (C_i, PD_i, FE_i)$, where C_i presents cloud computing framework ID and FE_i denotes the preprocessed and relevant features to be processed by cloud server for agricultural productivity prediction. The cloud servers store the preprocessed and relevant features and perform agricultural productivity prediction in our work. The edge servers are associated with the cloud that contains cache copies of the commonly accessed data inside cloud. If a user or farmer makes a query (i.e., agricultural productivity for a corresponding region), the respective edge server responds to user by the prediction result. This in turn minimizes the response time and also as the entire sensor data is not analyzed and stored inside the remote cloud servers, the overhead on the cloud incurred for agricultural productivity prediction is reduced.

1.1 Dataset Description

The Climate Change Impact on Agriculture Dataset obtained from <https://www.kaggle.com/datasets/waqi786/climate-change-impact-on-agriculture?resource=download> analyzes the influences of climate change on agricultural productivity across various regions comprises of data on precipitation, temperature and crop yields to understand how change in climate patterns influence agriculture. Table 1 given below lists the dataset description.

Table 1 Climate Change Impact on Agriculture Dataset description

S. No	Feature	Description	S. No	Feature	Description
1	Year	Analysis year	9	Extreme_weather_events	Occurrence of weather events
2	Country	Analyzed country	10	Irrigation Access_%	Irrigation accessed
3	Region	Geographical region	11	Pesticide use_KG_per_HA	Usage of pesticide
4	Crop_type	Type of crop	12	Fertilizer_use_KG_per_HA	Usage of fertilizer
5	Average temperature_C	Observed average temperature	13	Soil_health_index	Soil health index value
6	Total_precipitation_mm	Total precipitation	14	Adaptation_strategies	Strategies adapted
7	CO2_emission_mt	Total emission of CO2	15	Economic_impact_million USD	Impact of economy
8	Crop yield_mt_per_Ha	Total crop yield			

The data or records for this dataset have been obtained from several research studies and agricultural reports. The objective behind the collection of this data was to aggregate pertinent and updated information on climate variables and their influence on prediction of crop. The sources consist of sensor data acquired from climate databases, agricultural surveys, imparting an extensive view of climate change influences on distinct crops in different regions. Moreover to ensure both consistency and accuracy each sensor data point was carefully reviewed. Finally the dataset was then organized to impart a precise and accessible insight of how different climatic conditions impact productivity on agriculture across different regions and types of crop.

1.2 Kalman Bucy Riccati and Spatio-Temporal Regression based Feature Extraction

In this section Kalman Bucy Riccati and Spatio-Temporal Regression based Feature Extraction model is designed. This feature extraction model is designed in layer 2 by edge device. With the sensor data acquired from the layer 1 the edge device performs pre-processing and feature extraction process. Pre-processing is performed by the edge device in layer 1 by employing the Kalman Bucy Riccati Filter-based preprocessing. Followed by which feature extraction is performed by the edge device by utilizing Spatial and Temporal Regression based Feature Extraction model. Finally, the edge device sends processed and relevant and valuable data to layer 3. Figure 2 shows the structure of Kalman Bucy Riccati and Spatio-Temporal Regression based Feature Extraction model.

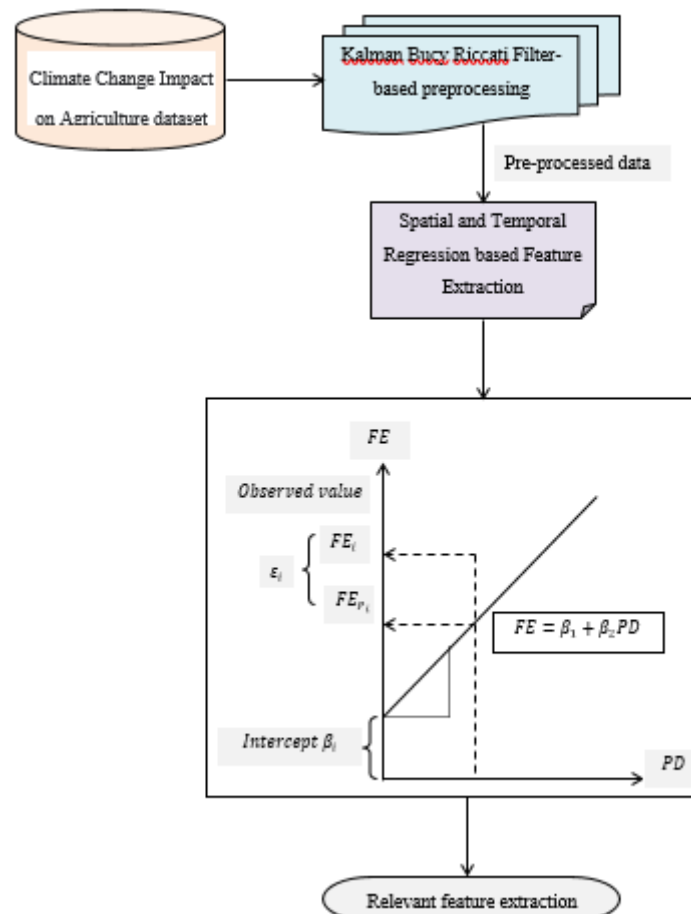


Figure 2 Structure of Kalman Bucy Riccati and Spatio-Temporal Regression based Feature Extraction model

As illustrated in the above figure the Kalman Bucy Riccati and Spatio-Temporal Regression based Feature Extraction model is split into two sections, namely, pre-processing and feature extraction. Pre-processing and Feature extraction employing Kalman Bucy Riccati Filter and Spatial and Temporal Regression is performed by the edge device in layer 2. The elaborate description is provided in the following sections.

1.2.1 Kalman Bucy Riccati Filter-based preprocessing (minimizes prediction time)

Kalman Bucy Riccati Filtering utilizes dynamic and continuous model and numerous continuous measurements obtained from sensors to model systems varying quantities (i.e. state) that is comparatively better than the estimate obtained employing only single measurement. Employing Kalman Bucy Filter-based preprocessing influence on global warming on agriculture estimates stochastic vector process (i.e. shifting climate patterns affecting agriculture) on the basis of the observations (i.e. samples obtained from raw dataset). The Kalman Bucy Riccati Filter deals efficiently with the uncertainty owing to noisy sensor data and estimates unmeasured states and processes outputs accordingly. Let us consider the linear continuous-time procedure as illustrated in the figure 3 given below.

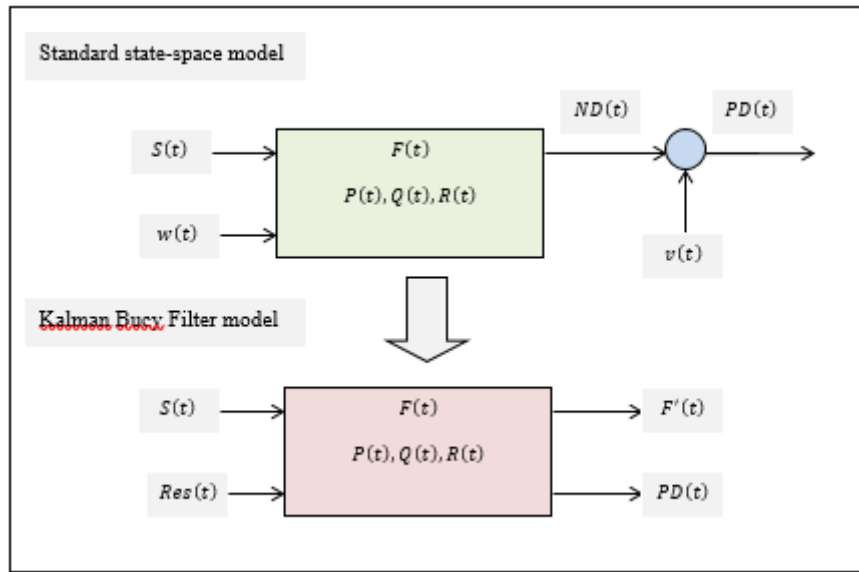


Figure 3 Structure of Kalman Bucy Riccati Filter-based preprocessing model

As shown in the above figure, the standard state-space for climatic change impact of agriculture dataset when substituted is mathematically formulated as given below.

$$F' = PF + QS + w \tag{1}$$

$$ND = RF \tag{2}$$

$$Res = ND + v \tag{3}$$

From the above equations (1), (2) and (3), ‘S’ represents the vector of inputs (i.e., samples) with ‘F’ denoting the actual state (i.e. climate change features influencing agriculture in the raw dataset), ‘ND’ denoting the vector of actual process outputs (i.e. noisy data), ‘Res’ representing the vector of measured processed outputs (i.e. preprocessed data for standard-space), ‘w’ and ‘v’ denoting process noise (i.e. preprocessing noise) and output noise (i.e. processed data) respectively. Now given the inputs, measured outputs, the objective of Kalman Bucy Filter-based preprocessing is to measure the unmeasured states and obtain the actual process outputs.

$$K = PR^T Ric \tag{4}$$

$$Res' = PF' + QS + K(Res - RF') \tag{5}$$

From the above equations (4) and (5), ‘PR^T’ and ‘K’, represents the covariance of measurement error and Kalman Bucy gain respectively. Finally with the above actual process outputs ‘Res’’, the state estimates are updated using the Riccati differential equation as given below.

$$PD = Res'(t) = S_0(t) + S_1(t)Res(t) + S_2(t)Res^2(t) \tag{6}$$

With the above obtained results ‘PD’ as given in equation (6) the pre-processed data is generated by the edge device in the layer 2.

1.2.2 Spatial and Temporal Regression based Feature Extraction

With the preprocessed data as input, a novel presented a novel Spatial and Temporal Regression model is applied to extract both spatial and temporal data for agricultural productivity prediction.

To start with the relationship between the independent and dependent variable has to be analyzed. Here the independent variable refers to the processed data ‘PD_{i1}, PD_{i2}, ..., PD_{ik}’ whereas the dependent variable denotes the output features to be extracted ‘FE₁, FE₂, ..., FE_n’. Then, the standard least square regression is generated as given below.

$$FE_i = \beta_0 + \sum_{k=1}^p \beta_k PD_{ik} + \varepsilon_i, i = 1, 2, \dots, N = FE = PD\beta + \varepsilon \tag{7}$$

From the above equation (7) the standard least square regression is formulated based on the intercept term ‘β₀’, regressive coefficients ‘β₁, β₂, ..., β_p’, sample size ‘N’, number of independent variables ‘p’ and error term ‘ε’ respectively. In our work, with the standard least square regression does not considering the local estimates, Spatial Regression function is introduced as given below.

$$SFE_i = \beta_0(Reg_i) + \sum_{k=1}^p \beta_k(Reg_i) PD_{ik} + \varepsilon_i \tag{8}$$

$$SFE = \begin{bmatrix} FE_1 \\ FE_2 \\ \dots \\ FE_n \end{bmatrix}; \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_n \end{bmatrix}; \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_n \end{bmatrix}; PD = \begin{bmatrix} 1 & PD_{11} & PD_{12} & \dots & PD_{1n} \\ 1 & PD_{11} & PD_{22} & \dots & PD_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ 1 & PD_{p1} & PD_{p2} & \dots & PD_{pn} \end{bmatrix} \quad (9)$$

From the above equation (9) the evaluation of parameter ‘ β ’ is written as given below.

$$\beta' = (PD^T PD)^{-1} PD^T SFE \quad (10)$$

Followed by which the Spatial Regression function to the standard least square regression is modeled as given below.

$$SFE_i = \beta_0(Reg_i) + \sum_{k=1}^p \beta_k(Reg_i) PD_{ik} + \varepsilon_i \quad (11)$$

From the above equation (11), ‘ $p_i q_i$ ’ represent, the coordinates of sample ‘ i ’ with ‘ $\beta_0(p_i q_i)$ ’ denoting the constant, ‘ $\beta_k(Reg_i)$ ’ denoting the coefficient of ‘ $k - th$ ’ independent variable at geographical region ‘ Reg_i ’ respectively. Then the extracted value ‘ SFE'_i ’ of sample ‘ i ’ is then represented as given below.

$$SFE'_i = PD_i^T \beta'(Reg_i) = PD_i^T (PD_i^T PD)^{-1} PD^T FE \quad (12)$$

From the above equation (12), ‘ PD_i ’ denotes the vector of ‘ $i - th$ ’ row of matrix ‘ PD ’, then utilizing the matrix notation the spatial pattern extracted values for agriculture productivity prediction is represented as given below.

$$SFE' = \begin{bmatrix} PD_1^T [PD^T (Reg_i) PD]^{-1} PD^T (Reg_i) \\ PD_2^T [PD^T (Reg_i) PD]^{-1} PD^T (Reg_i) \\ \dots \\ PD_n^T [PD^T (Reg_i) PD]^{-1} PD^T (Reg_i) \end{bmatrix} \quad (13)$$

Followed by which the Temporal Regression function is introduced as given below.

$$Res_i = \beta_0(t_i) + \sum_{k=1}^p \beta_k(t_i) PD_{ik} + \varepsilon_i \quad (14)$$

From the above equation (14) ‘ t_i ’ represents the time coordinate for corresponding sample ‘ i ’, then the coefficient of ‘ $i - th$ ’ independent variable at time ‘ t_i ’ is represented as given below.

$$\beta'(t) = (PD^T(t) PD)^{-1} PD^T(t) FE \quad (15)$$

Finally the spatial and temporal features extracted results are obtained as given below.

$$FE = Res_i, \beta'(t) \quad (16)$$

From the above equation (16) the features extracted results ‘ FE ’, are obtained by combining the spatial ‘ Res_i ’ and temporal features ‘ $\beta'(t)$ ’ together.

Support Vector Regression-based Classification for crop yield prediction

Finally with the objective of improving agriculture productivity prediction Support Vector Regression function is applied to the processed valuable and relevant data. Let us construct a sample set ‘ $SS = \{x_1, x_2, \dots, x_n\}$, where $x \in PD_i[FE_i]$ ’ then the target of classified results is said to be ‘ $Y_i \in Cl$ ’, then using sample set and the target of classified results is expressed in the form of matrix as given below.

$$Mat_i = \begin{pmatrix} SS_i \\ Cl_i \end{pmatrix} \quad (17)$$

Then using a support vector regression fitness function the optimality of classified results is obtained. The support vector regression fitness function is used in determining whether the current classified results are optimal result or not. The support vector regression fitness function of agriculture productivity prediction is set as given below.

$$Fitness = \frac{N}{\sum_{i=1}^n (EO_i - AO_i)^2} \quad (18)$$

From the above equation (18) fitness ‘ $Fitness$ ’, here represents the fitness function of agriculture productivity prediction with ‘ EO_i ’ and ‘ AO_i ’ representing the expected output and actual output respectively. Moreover the fitness function applied here being a line function of mean square error and reciprocal between expected output and actual output, the smaller the error the larger the corresponding fitness value is and vice versa.

The pseudo code representation of Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) based Crop yield prediction is given below.

Input: Dataset ‘ DS ’, Samples or sensors ‘ $S = \{S_1, S_2, \dots, S_N\}$ ’, Features ‘ $F = \{F_1, F_2, \dots, F_n\}$ ’
Output: Computationally efficient preprocessed data with relevant feature for precise and accurate prediction
Step 1: Initialize ‘ $N = 50000$ ’, ‘ $n = 15$ ’
Step 2: Begin
Step 3: For each Dataset ‘ DS ’ with Samples or sensors ‘ S ’ and Features ‘ F ’

//Preprocessing

Step 4: Mathematically formulate standard state-space for climatic change impact of agriculture as given in (1), (2) and (3)

Step 5: Measure the unmeasured states and obtain the actual process outputs as given in (4) and (5)

Step 6: Perform state estimates update by applying Riccati differential equation as given in (6)

Step 7: **Return** preprocessed data '*PD*'

Step 8: **End for**

//Feature extraction

Step 9: **For** each Dataset '*DS*' with Samples or sensors '*S*', Features '*F*' and preprocessed data '*PD*'

//Spatial pattern extracted values for agriculture productivity prediction

Step 11: Formulate standard least square regression for processed data as given in (7)

Step 12: Formulate Spatial Regression function for processed data as given in (8), (9) and (10)

Step 13: Formulate Spatial Regression function to the standard least square regression as given in (11)

Step 14: **Obtain extracted value** (i.e. spatial) ' SFE'_i ' of sample '*i*' and matrix representation as given in (12) and (13)

Step 15: **End for**

Step 16: **For** each Dataset '*DS*' with Samples or sensor '*S*', Features '*F*' and preprocessed data '*PD*'

//Temporal pattern extracted values for agriculture productivity prediction

Step 17: Formulate Temporal Regression function as given in (14)

Step 18: Return the coefficient of '*i - th*' independent variable at time ' t_i ' as given in (15)

Step 19: Obtain extracted value (i.e. temporal) as given in (16)

Step 20: **Return feature extracted results** '*FE*'

Step 21: **End for**

//Classification

Step 22: **For** each Dataset '*DS*' with Samples or sensor '*S*', Features '*F*', preprocessed data '*PD*' and feature extracted results '*FE*'

Step 23: Obtain target of classified results is expressed in the form of matrix as given in (17)

Step 24: Measure fitness function as given in (18)

Step 25: **End for**

Step 26: **End**

Algorithm 1 Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) based Crop yield prediction

As given in the above algorithm, with the climatic change impact of agriculture dataset as input the raw samples are subjected to standard state-space model that in turn obtains the effects of climate change continuously. Also the unmeasured states are evolved with the objective of controlling the samples with respect to different features. Next, Riccati differential equation is applied to perform the updates or fine tune that in turn ensures robust stabilization while analyzing the climate change impact on agriculture. This in turn returns computationally efficient processed data in layer 2 or the edge device. With the pre-processed data obtained are subjected to Spatial and Temporal Regression function. Here, both the spatial (i.e. geographic region) and temporal (i.e. based on time – average temperature, total precipitation and CO₂ emission) are subjected to machine learning based regression function that in turn returns valuable and relevant data (i.e. feature) to layer 3. Finally in the third layer or the cloud server performs the task of classification for crop yield prediction. Here, with the aid of fitness function the actual and target values are compared to generate accurate and precision crop yield prediction results.

EXPERIMENTAL SETUP

In this section, simulations and validations are performed for producing crop yield prediction results using Climate Change Impact on Agriculture Dataset as input obtained from <https://www.kaggle.com/datasets/waqi786/climate-change-impact-on-agriculture?resource=download>. An elaborate comparison between the proposed Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) based Crop yield prediction and existing methods, Edge Computing with auction and Fuzzy Neural Network (EC-aFNN) [1] and Multi Layer Perceptron Sperm Swarm Optimization (MLP-SSO) [2] using Edge Cloud Simulator tool and Python programming language.

Simulations are performed using Climate Change Impact on Agriculture Dataset and validated different metrics, prediction accuracy, precision, recall, prediction time and prediction error.

DISCUSSION

In this section performance metrics in terms of prediction accuracy, precision, recall, prediction time and prediction error are discussed using the proposed Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) based Crop yield prediction and two existing methods, Edge Computing with auction and Fuzzy Neural Network (EC-aFNN) [1] and Multi Layer Perceptron Sperm Swarm Optimization (MLP-SSO) [2]. To ensure fair comparison between the proposed and existing methods, similar samples of data are utilized for both analysis and validation purpose.

Performance analysis of precision, recall and accuracy

The precision is measured as given below.

$$Pre = \frac{TP}{TP+FP} \tag{19}$$

From the above equation (19), precision ‘Pre’ is evaluated on the basis of the true positive rate ‘TP’ and false positive rate ‘FP’. Recall rate are said to be the measurements of quantity whereas the precision rate are said to be the measurements of quality. Consequently, higher precision level refers to that the algorithm being designed generates more relevant results upon comparison to the irrelevant results. Next, the performance metric, recall is measured as given below.

$$Rec = \frac{TP}{TP+FN} \tag{20}$$

From the above equation (20), recall ‘Rec’ is measured employing the true positive rate ‘TP’ and false negative rate ‘FN’ respectively. When compared to precision, recall is evaluated based on the ratio of relevant crop yield made by a search to the total number of relevant crop yields available. Finally, accuracy is defined as the model’s overall veracity and is evaluated as the sum of original crop yield parameters divided by the total number of crop yield parameters. The accuracy rate is measured as given below.

$$Acc = \frac{TN+TP}{TN+TP+FN+FP} \tag{21}$$

From the above equation (21), accuracy ‘Acc’ is evaluated on the basis of the true positive rate ‘TP’, true negative rate ‘TN’, false positive ‘FP’ and false negative rate ‘FN’ respectively. In this study, Python a high-level general-purpose programming language along with Edge Cloud Simulator tool is employed in measuring crop yield prediction. The proposed KRST-SVR method outperforms the existing Edge Computing with auction and Fuzzy Neural Network (EC-aFNN) [1] and Multi Layer Perceptron Sperm Swarm Optimization (MLP-SSO) [2] for crop yield prediction in terms of precision, recall and accuracy. The values of the present and planned systems are compared in table 2.

Table 2 Comparing proposed KRST-SVR and existing method EC-aFNN [1], MLP-SSO [2] values in terms of precision, recall and accuracy

Samples	Precision			Recall			Accuracy		
	KRST-SVR	EC-aFNN [1]	MLP-SSO [2]	KRST-SVR	EC-aFNN [1]	MLP-SSO [2]	KRST-SVR	EC-aFNN [1]	MLP-SSO [2]
5000	0.98	0.96	0.93	0.99	0.99	0.99	0.98	0.96	0.93
10000	0.96	0.91	0.85	0.95	0.85	0.8	0.96	0.9	0.85
15000	0.95	0.9	0.84	0.92	0.82	0.77	0.93	0.87	0.82
20000	0.93	0.88	0.82	0.9	0.8	0.75	0.9	0.84	0.79
25000	0.91	0.86	0.8	0.85	0.75	0.7	0.88	0.82	0.75
30000	0.9	0.85	0.79	0.87	0.77	0.72	0.91	0.85	0.8
35000	0.92	0.87	0.81	0.9	0.8	0.75	0.93	0.87	0.82
40000	0.94	0.89	0.83	0.93	0.83	0.78	0.88	0.82	0.77
45000	0.96	0.91	0.85	0.9	0.8	0.75	0.9	0.84	0.79
50000	0.97	0.92	0.86	0.94	0.84	0.79	0.92	0.86	0.81

From the above table with 5000 samples involved in the simulation for analyzing the impact of global warming in agriculture crop yield prediction and with 48500 samples with proper crop yield prediction being made and 500

samples provided with improper crop yield prediction using MF-KDPNN, 47500 samples with proper crop yield prediction being made and 1500 samples provided with improper crop yield prediction using EC-aFNN [1] and finally, 46000 samples with proper crop yield prediction being made and 3000 samples provided with improper crop yield prediction using MLP-SSO [2], the precision was measured and plotted in graph. In a similar manner, with 5000 samples involved in the simulation for analyzing the impact of global warming on agriculture crop yield prediction and with 48500 samples with proper crop yield prediction being made and 750 samples provided with false crop yield prediction using MF-KDPNN, 47500 samples with proper crop yield prediction being made and 700 samples provided with false crop yield prediction using EC-aFNN [1] and finally, 46000 samples with proper crop yield prediction being made and 600 samples provided with false crop yield prediction using MLP-SSO [2], the recall is measured and plotted in graph.

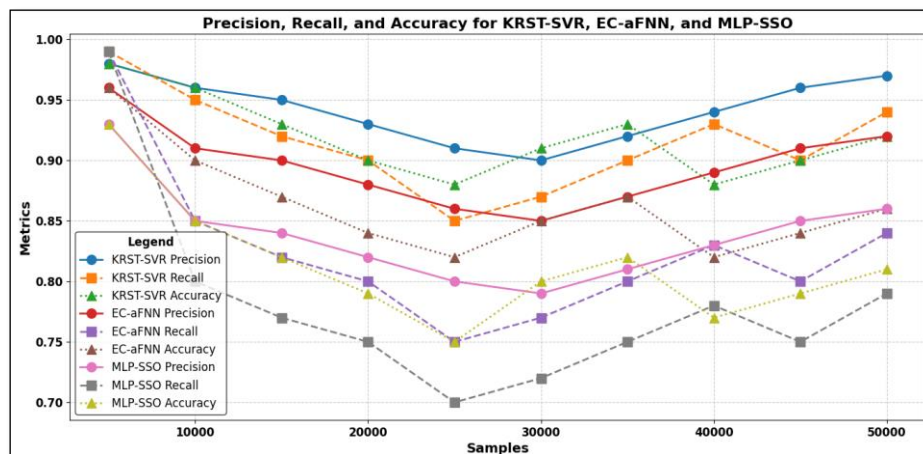


Figure 4 Precision, recall and accuracy performance metrics

Figure 4 given above shows the graphical representations of precision, recall and accuracy using the proposed KRST-SVR method and two existing methods, EC-aFNN [1], MLP-SSO [2] [2] for analyzing the impact of agriculture crop yield prediction. As shown in above figure, the precision of the comparison measure is obtained utilizing both the existing and proposed methods. The proposed KRST-SVR method and two existing methods [1], [2] are selected on the x-axis, and the precision, recall and accuracy value is plotted on the y-axis. For the given crop yield dataset, traditional methods such as the [1] and [2] have a lower precision, whereas the proposed KRST-SVR method has a higher precision. As a result, proposed KRST-SVR method boosts the accuracy of crop yield prediction by predicting crop types in an accurate manner despite impact of global warming in agriculture.

Also as shown in the above figure, the recall of the comparison measure is measured employing both the existing [1], [2] and new proposed KRST-SVR method. The recall value of three methods is plotted along the y-axis and on the other hand the three methods are plotted along the x-axis. For the presented climate change impact on agriculture dataset, the traditional methods such as [1] and [2] yield a lower recall, and on the other hand the proposed KRST-SVR method yields a higher recall. As a result, the proposed KRST-SVR method despite change in climate observed improves crop yield prediction accuracy by selecting crops precisely.

Finally, the crop yield prediction accuracy or accuracy of the comparison measure is measured employing both the proposed KRST-SVR method and current methods, [1] and [2]. On the x-axis, three methods are selected, whereas on the y-axis represents the accuracy value. Existing methods such as [1] and [2] gave lower accuracy for given climate change impact on agriculture dataset, whereas the proposed KRST-SVR method provides higher accuracy.

The reason for the improvement in terms of precision, recall and accuracy was due to the application of Support Vector Regression based classifier model in layer 3 via cloud server for crop yield prediction. By applying this model, the cloud server in layer 3 obtained both pre-processed data along with relevant features for performing further classification. Finally the classification for crop yield prediction was done using support vector regression fitness function. This in turn improved the precision rate of proposed KRST-SVR method by 5% compared to [1] and 13% compared to [2]. Second, both spatial geographic region and temporal factors, average temperature, total

precipitation and CO2 emission were extracted and subjected to machine learning based regression function that in turn returns valuable and relevant data for final classification process. This in turn improved the recall rate of proposed KRST-SVR method by 11% compared to [1] and 18% compared to [2] and finally boosted the accuracy rate of proposed KRST-SVR method by 7% compared to [1] and 13% compared to [2] respectively.

Performance analysis of prediction time

In this section the impact of global warming or change in climate on agriculture crop yield prediction time or training time involved in crop yield prediction is measured as given below.

$$PT = \sum_{i=1}^N S_i * Time (Fitness[i.e for crop yield prediction]) \tag{22}$$

From the above equation (22) the prediction time ‘PT’ is measured on the basis of the samples taken into consideration ‘ S_i ’ for simulation purpose and the actual time consumed in the process of analyzing the impact of global warming or change in climate on agriculture crop yield prediction ‘ $Time (Fitness[i.e for crop yield prediction])$ ’. It is measured in terms of milliseconds (ms). The values of the present and planned systems in terms of prediction time using the proposed KRST-SVR method and the existing EC-aFNN [1], MLP-SSO [2] for yield prediction is provided in table 3.

Table 3 Comparing proposed KRST-SVR and existing method EC-aFNN [1], MLP-SSO [2] values in terms of prediction time

Samples	Prediction time (ms)		
	KRST-SVR	EC-aFNN [1]	MLP-SSO [2]
5000	175	235	260
10000	205	255	285
15000	215	265	295
20000	245	295	325
25000	280	330	360
30000	255	305	335
35000	225	275	305
40000	200	250	285
45000	235	285	315
50000	280	315	345

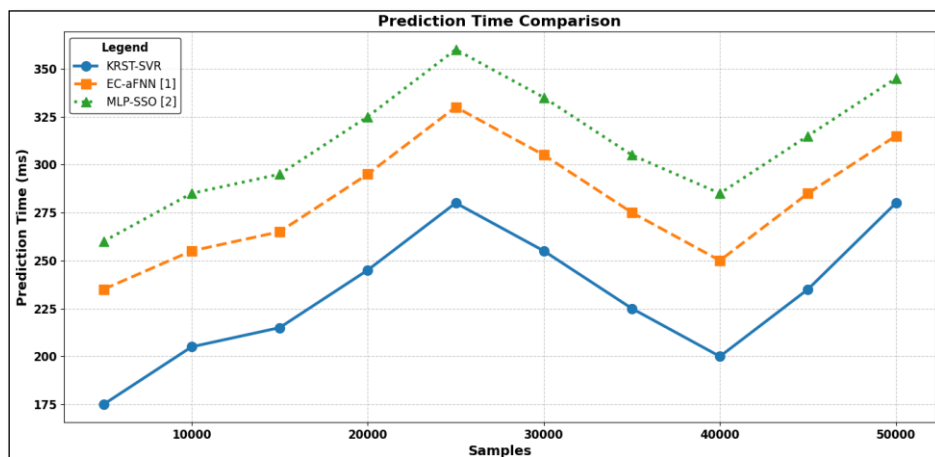


Figure 5 Training time performance metrics

When the proposed method executes faster the method is said to be improved as illustrated in figure 5. The proposed and existing methods are used in comparing the prediction time for analyzing the impact of global warming on agriculture crop yield prediction of the comparative measure, as seen in figure. The samples ranging between 5000 and 50000 are characterized on the x-axis, and on the other hand the prediction times are plotted on the y-axis. The existing methods, such as the existing EC-aFNN [1], MLP-SSO [2] for analyzing the impact

of global warming on agriculture crop yield prediction have a longer prediction time, whereas the proposed KRST-SVR has a shorter training time for the crop yield prediction dataset. As a result, the proposed KRST-SVR method improves crop yield prediction time and minimizes the error rate by recommending crop types appropriately. The reason for the improvement was due to the application of Kalman Bucy Riccati Filter based pre-processing model. By applying this model, the pre-processed data were obtained by modeling systems varying quantities (i.e. state) that is comparatively better than estimate obtained employing only single measurement. Also by applying stochastic vector process (i.e. measuring shifting climate patterns affecting agriculture) the overall pre-processed data were obtained that in turn reduced prediction time of the proposed KRST-SVR method by 18% compared to [1] and 26% compared to [2].

1.3 Performance analysis of prediction error

Finally in this section the prediction error rate is measured as given below.

$$PE = \sum_{i=1}^N \frac{S_{WP}}{S_i} \tag{23}$$

From the above equation (23) the prediction error rate ‘PE’ is evaluated on the basis of the samples involved in the simulation process ‘ S_i ’ and the samples wrongly predicted ‘ S_{WP} ’. It is measured in terms of percentage (%). The values of the present and planned systems in terms of prediction error rate using the proposed KRST-SVR method and the EC-aFNN [1], MLP-SSO [2] for analyzing the impact of global warming in agriculture crop yield prediction is provided in table 4.

Table 4 Comparing proposed KRST-SVR and existing method EC-aFNN [1], MLP-SSO [2] values in terms of prediction error

Samples	Prediction error (%)		
	KRST-SVR	EC-aFNN [1]	MLP-SSO [2]
5000	5	9	15
10000	6.35	10.45	15.85
15000	7	11	16
20000	9	12.35	16.35
25000	10.25	14	17
30000	9	12.15	15.35
35000	8.35	11	13.15
40000	8	10.85	11
45000	8.85	11	11.35
50000	8.15	10	10.55

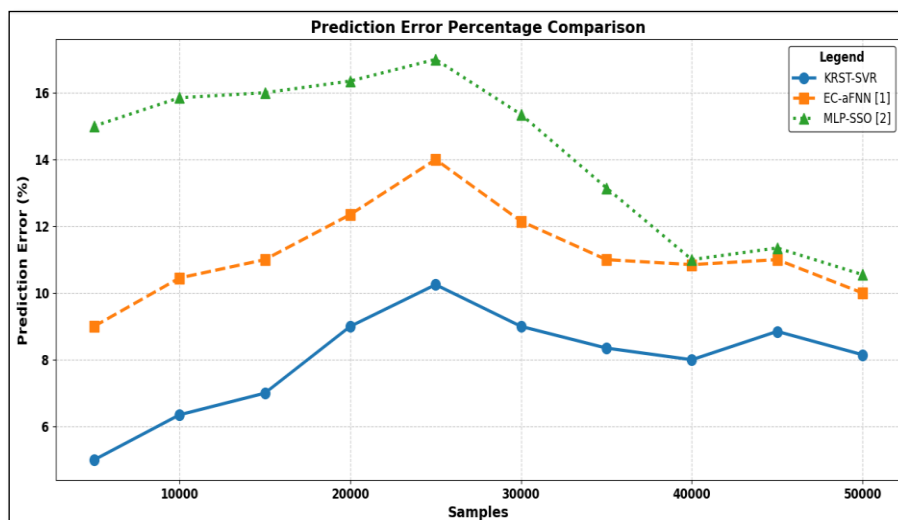


Figure 6 Prediction error performance metrics

Finally in the above figure 6 the graphical representation of crop yield prediction error rate using the three methods, KRST-SVR, EC-aFNN [1], MLP-SSO [2] for analyzing the impact of agriculture on crop yield prediction are provided. With x-axis representing the samples ranging between 5000 and 50000, y-axis denotes the prediction error rate by substituting the values in equation 23. Also from the above figure it is illustrative that the prediction error rate is neither said to be increasing nor decreasing with the increase in samples. This is evident from the above table where with 30000 samples involved the prediction error rate using the three methods were observed to be 9%, 12.15% and 15.35% whereas when applied with 35000 samples, the prediction error rate using the three methods were found to be 8.35%, 11% and 13.15% respectively. Also comparative analysis showed better results using proposed KRST-SVR method than when compared to [1] and [2]. This is evident from the sample 5000 where the wrong prediction using the three methods was found to be 250, 450 and 750 accordingly the prediction error rate was found to be 5%, 9% and 15% respectively. With this the prediction error rate using the proposed KRST-SVR method was found to be comparatively lesser than [1] and [2]. The reason behind the improvement was due to the application of Spatial and Temporal Regression based Feature Extraction model. By applying this model, initially, the standard least square regression as though did not took into consideration the local estimates, Spatial Regression function employed in our work was employed to return spatial efficient features. Next, Temporal Regression function was applied for extracting temporal efficient features like, average temperature, total precipitation and CO₂ emission. This in turn obtained temporal efficient features. Finally by combining the temporal and spatial efficient features for further processing aided in improving overall prediction accuracy. With this the prediction error using the proposed KRST-SVR method was said to be reduced by 29% compared to [1] and 42% compared to [2].

CONCLUSION

In this study the impact of global warming on agriculture crop yield prediction using Kalman Riccati Spatio-Temporal Support Vector Regression (KRST-SVR) is proposed for recommending accurate crop in a precise and low training time. With the edge computing combined with machine learning model, three layers are employed. In the first layer of edge computing the data are obtained from the Climate Change Impact on Agriculture Dataset. Next in the second layer of edge computing the edge device performed the task of pre-processing and feature extraction by employing Kalman Bucy Riccati Filter-based preprocessing and Spatial and Temporal Regression based Feature Extraction model. Finally, the results of processed data along with relevant features for classification were fed as input to the cloud server via the third layer of edge computing. In the third layer the actual classification process was performed via support vector regression fitness function to generate the prediction results. The Climate Change Impact on Agriculture Dataset was utilized for experimental assessment and the results were also compared with traditional state-of-the-art methods. The proposed KRST-SVR method performs better on the whole in terms of precision, recall, accuracy, prediction time and prediction error.

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