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An Innovative Hybrid Approach for Predicting Crop Yields across Diverse States and Crops

M. Revathi[1], Dr. N. Kanya[2], Dr. Victo Sudha George[3]
[1]Research scholar, Department of Computer Science and Engineering, Dr. M.G.R. Educational and Research Institute, Chennai. Email id: revathi.cse@drmgrdu.ac.in@gmail.com
[2]Professor, Department of Information Technology, Dr. M.G.R. Educational and Research Institute, Chennai, India. Email id: kanya.v@drmgrdu.ac.in
[3]Professor, Department of Computer Science and Engineering, Dr. M.G.R. Educational and Research Institute, Chennai, India. Email id: victosudhageorge@drmgrdu.ac.in

Abstract: The use of machine learning and deep learning may help estimate crops by automatically extracting attributes and learning from information. Meanwhile, smart farming technology aids farmers in increasing yields by isolating key factors in plant development. In this study, we present a unique hybrid approach (SLR) for predicting crops by extracting key characteristics from SVM (Support Vector Machine), LSTM (Long-Short Term Memory), or RNN (Recurrent Neural Network). Here, we experimented with crops from a variety of states to estimate their potential yields in quintals per hectare. The suggested method has a37.45 percent precision rate, an 80.00 percent recall rate, a51.01 percent fscore, a93.64 percent specificity rate, and an accuracy rate of 93.02 percent.

Keywords: Crop yield, SVM, LSTM, RNN, SLR.

I. INTRODUCTION

Agriculture is a vital component of human life since it provides the majority of people with food and shelter [1]. With a rapidly expanding human population, it's crucial to keep tabs on and predict harvest yields. Agriculture is to be monitored as well as optimized to support a nation's food security & economic prosperity. Any nation's agricultural policy should prioritize maximum crop production per unit of input. It's not easy to predict harvest since so many variables come into play (weather, soil, crop cultivar, cultivation methods, crop form, texture, color, surface texture, and so on) [1].

Agriculture is the study & practice of farming, which includes the preparation of land for planting crops and raising livestock. Despite their expertise in farming, farmers in rural regions have limited access to information about the latest advances in science and technology. The use of technology in agriculture is essential if we are to see a rise in output. In addition to increasing output, it will also aid in enhancing crop quality. The impacts of environmental factors such as soil temperature, humidity, pH, and moisture on agricultural yields are the subject of intensive study. However, farmers' lack of awareness of such advances in science has slowed the pace of agricultural innovation [2]. The meteorological and environmental elements, such as seasonal precipitation as well as temperature changes, daily temperature ranges, and the water cycle between soil and atmosphere, have a significant impact on crop development, quality, and yield. New possibilities for analyzing crop variability are opening up as precision agriculture matures via the monitoring of key components [3]. These farming methods not only affect the quality of the land, water, and air but also alter the seasonal climatic conditions, leading to food insecurity [4].

Because of population growth and climate change, protecting the world's food supply has become an urgent priority. To adapt to shifting weather patterns and the competitive nature of today's agricultural market, today's farmers must make some tough choices. Farmers may make more informed decisions about their crops if they have access to up-to-date and reliable data on factors like weather, soil, fertilizer, and pesticide use. If the circumstances are favorable for crop production, this might help them achieve higher yields, and if they are not, it could help them suffer less loss. Numerous research studies have looked at how ICT may be used to enhance agricultural production prediction, with effective implementation in a range of climate conditions [5].

The application of machine learning is a practical approach that can improve yield prediction across a wide variety of characteristics. It's a branch of AI that emphasizes learning new things. Machine learning (ML) may mine data for hidden insights by spotting connections and patterns. Models must be educated on data sets that depict outcomes based on historical experience. During the training phase, the parameters of the prediction model are determined by analyzing historical data. During the testing process, outcomes are evaluated using some of the historical information that was not used for preparation. Depending on the focus of the study and the questions that need answering, an ML model may be descriptive or predictive. Predictive models use historical data to make forecasts about the future. On the other hand, descriptive templates are useful for describing the current state of affairs or historical events. Predicting agricultural yields, selecting which crops to plant, and planning for the growing season might all benefit from the use of machine learning. The work in predicting agricultural yields was aided by the use of many machine learning algorithms. Recent years have seen an uptick in the use of machine learning techniques including multivariate regression, decision trees, association rule mining, or artificial neural networks for forecasting crop yields. In the realms of classification and regression, support vector machines (SVM) discovered extensive usage. Vapnik and Vladimir presented the support vector machine (SVM) as a learning device with a minimum construction risk. Hinton and Salakhutdinov introduced deep learning (DL) as a new area of study in the science of machine learning. Fundamentally, it's all about laying the groundwork for and enhancing the human brain's analytical and learning neural network. Interpret the data in a way that is analogous to how the human brain does it by studying the properties of each layer in the neural network [6, 7], [8].

When trying to develop a high-performance prediction model, ML research presents several obstacles. The algorithms and underlying platforms you choose must be able to cope with the amount of data you want to process, and you must choose the proper algorithms for the situation at hand. After the temporal data series has been normalized, it is input into a neural network that recurs RNN has seen extensive use for dealing with sequence data. Sequence classification, temporal information forecasts, and other applications may all benefit from their ability to not only detect temporal correlations between data samples but also to extract the best representative characteristics for that sequence. [9] [10].

This research investigates the use of machine learning as well as deep learning algorithms to forecast agricultural output.

II. LITERATURE SURVEY

The technique presented to forecast agricultural production from Internet databases was developed by Devdatta A. Bondre et al [11]. Machine learning methods such as Support Vector Machine & Random Forest are used to agricultural data to determine the optimal fertilizer for each crop. In this study, we concentrate on developing a model for potential crop production forecasting. It offered a quick look at how machine learning may be used to forecast agricultural yields.

To improve the accuracy of their yield predictions, Potnuru Sai Nishant et al. [12] suggested a system that employs cutting-edge regression methods such as the Kernel Ridge, Lasso, and ENet algorithms, as well as the idea of stacking regression. They use layered regression, and the resulting estimate is much less precise than when the models were used singly. Current results are available via a web application; further development would include adapting the system so that farmers may use it on mobile devices and translating it into their native tongue.

KodimalarPalanivel et al. [13] looked at the accuracy of many machine learning systems for estimating harvests. Predicting agricultural yields with the use of machine learning has been suggested as part of the big data computation paradigm. Root-mean-square error and other measures of machine learning algorithm performance are analyzed. Predictive machine learning algorithms will be examined, but it is also intended to look at how big data approaches could affect the accuracy of such predictions. For this, the authors offer a conceptual method. The same is also being put into practice.

To assist farmers in determining the condition of their soil, RushikaGhadge et al. [14] devised a technique based on data mining analysis. Therefore, the system prioritizes analyzing soil quality to foretell cultivatable crops based on soil type and optimize crop production via fertilizer recommendations. The best possible outcome in terms of accuracy is returned by the system, which does this using supervised & unsupervised Machine Learning methods. Both algorithms' outputs will be compared to determine which one produces more reliable results, and then that method will be used.

By fusing the temporal convolutional network (TCN) or the recurrent neural network (RNN), Liyun Gong et al. [15] created a novel method for predicting greenhouse crop yields. Multiple datasets collected from various authentic greenhouse settings for tomato growth have been used to perform in-depth analyses of the suggested method. It is shown that the suggested methodology outperforms both standard machine learning approaches in addition to classical deep neural networks in predicting crop yields by calculating the root mean square errors (RMSEs) in the expected and actual yields. Furthermore, the experimental investigation confirms that past yield data is the most crucial aspect in making precise predictions about future crop yields.

The model presented by Sonal Agarwal et al. [16] is improved via the use of deep learning methods, and in addition to crop prediction, unambiguous information is acquired on the quantities of soil elements required, along with their costs. When compared to the current model, it improves precision. It looks at the data and gives the farmers an idea of what they may harvest, which boosts their income.

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Predicting an appropriate yield requires thinking about the land's climate and soil. The purpose of this paper is to provide a Python-based system that uses strategic thinking to foresee the most profitable harvest under certain circumstances and keep costs to a minimum. In this work, the SVM algorithm is employed for Machine Learning, while the LSTM and RNN algorithms are used for Deep Learning.

III. PROPOSED METHOD

To improve the accuracy of yields of crop prediction systems, this study uses a statistical approach that combines the SVM, LSTM, & RNN methods, each of which contributes a unique characteristic to the overall forecast. The optimal performance of each strategy is evaluated independently. A merged algorithm, dubbed SLR, is developed towards the end.

Apple, Banana, Black gram, chickpea, coconut, coffee, cotton, grapes, jute, kidney bean, lentil, maize, mango, moth beans, mung bean, muskmelon, orange, papaya, pigeon beans, pomegranate, watermelon from Various states of India. The information compiled here consists of their support price, nitrogen, phosphorous pentoxide, and Potassium oxide ratio as n-soil, P-soil, and K-soil, Temperature, humidity, PH, rainfall, and crop details

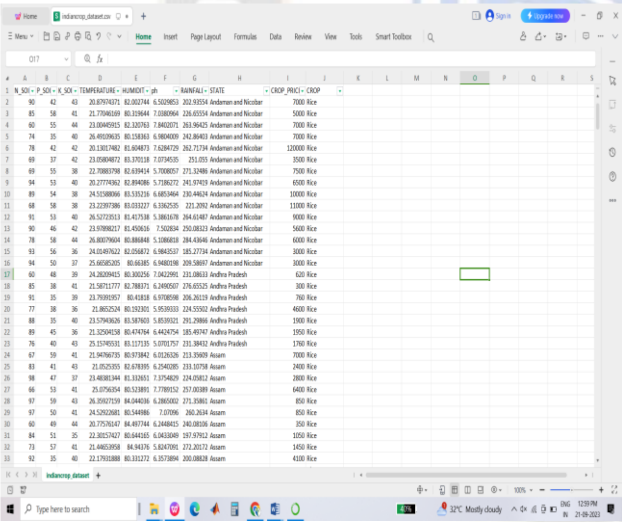

FIGURE1. Sample dataset

Data Preprocessing:

Data is tested for null values and replaced with zeros. And then all Strings are converted to numerical data. This step is followed in almost all types of data processing techniques.

Data Visualization

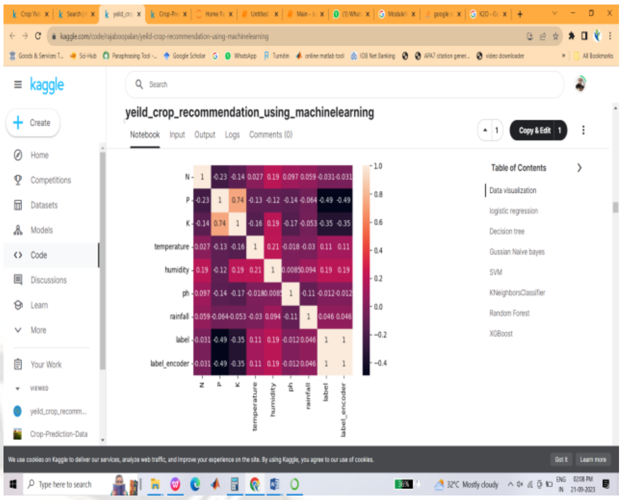

Figure 2.Cross-correlation of given features

i. *SVM*

Classification and regression issues are common places for support vector machines (SVM). Vapnik and Vladimir (1995) [4] introduced the support vector machine (SVM), a machine that learns based on low construction risk. The purpose of the support vector apparatus is to acquire a non-linear property by method of the function of the kernel. The SVM used to predict harvest yield is called support vector regression. Kernel & polynomial functions are the most common types of radial basis functions employed [1].

In high or infinite dimensional spaces, support vector machines (SVMs) generate hyperplanes that may be used for classification, regression, and other purposes. In general, the larger the edge, the lower the speculative blunder of the classifier, therefore the hyperplane with the greatest separation to the closest prepared information goal of any class will provide the best partition. To keep the computational load to an acceptable level, the SVM strategy makes use of mappings to ensure that the minor items will be computed concerning the first-degree variable [5].

$$c(xx, yy, f(xx)) = \begin{cases} 0, & \text{if } yy * f(xx) \geq 1 \\ 1 - yy * f(xx), & \text{else Hinge loss function} \end{cases}$$

$$c(xx, yy, f(xx)) = \begin{cases} 0, & \text{if } yy * f(xx) \geq 1 \\ 1 - yy * f(xx), & \text{else Hinge loss function} \end{cases}$$

(1)

Utilizing the Hinge function, we may amplify and enhance the sharpness of an area between the information point as well as the hyperplane. Hyperplanes xx and yy exist. If the projected and actual values have the same sign, the cost is zero; otherwise, the absence value is determined. Adding the regularization function to a Hinge loss function [8] helps to strike a balance between the regularized limits. Using the SVM method, we may generate functions from a collection

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of annotated training data. These procedures may take the form of a classification or a more broad regression. In addition to its use in agricultural yield prediction, support vector machines (SVMs) have been used to shed light on crop response patterns about climatic circumstances. Support Vector Machine, a machine learning technique based on discretization, was applied to the task of classifying agricultural datasets.

ii. *LSTM*

The recurrent neural network (RNN) with long short-term memory (LSTM) has the capacity for long-term dependencies. The neural network is a set of algorithms that attempt to simulate the way the human brain operates to recognize and exploit patterns. A recurrent neural network (RNN) is only a feedforward neural network that has its memory. Because of its recurring nature, RNN produces the same result regardless of the data source [8]. However, the result of the current calculation heavily relies on the results of previous computations. LSTMs feature feedback connections that may be used to create a more conventional feed-forward neural network. LSTMs excel in processing sequences of data and are hence well-suited for text, voice, and general time series [17].

In LSTM architectures, ht represents the current hidden state, $ht{-}1$ represents the state from the previous step, and xt is dependent on external input. There are three gates and one layer in LSTM architectures. These gates and the inner workings of the layer. Forgetting, entering, and leaving gates at time t are denoted by the notations ft, it, and ot respectively. The state layer is also represented by the gt symbol [20].

$$ft = \sigma(+ Ufh_{t-1} + bf)ft = \sigma(+ Ufh_{t-1} + bf) \quad (2)$$

$$it = \sigma(W_i X_t + Uih_{t-1} + bt)$$
$$it = \sigma(W_i X_t + Uih_{t-1} + bt) \quad (3)$$

$$ot = \sigma(W_o X_t + Uoh_{t-1} + bo)$$
$$ot = \sigma(W_o X_t + Uoh_{t-1} + bo) \quad (4)$$

$$gt = th(W_g X_t + Rgh_{t-1} + bg)$$
$$gt = th(W_g X_t + Rgh_{t-1} + bg) \quad (5)$$

Sequence prediction is a primary use of LSTM networks. To simplify, think of LSTM as a network with extra loops. Not only that, but LSTM is a subclass of RNN algorithms. In contrast to MLP networks, LSTMs have an internal state, recognize temporal structure in inputs, simulate parallel input series, and process inputs of varying lengths to produce outputs of varying complexity. The smallest logical unit of an LSTM is the memory cell [9]. To solve the long-term correlation problem in recurrent neural networks, Long Short-Term Memory Models (LSTMMs) are implemented. Without breaking up the data into individual pieces, they analyze the full sequence at once, remembering important details from the prior data that aid in understanding the current data. We were also able to classify the data with a high degree of precision, which helped us anticipate crop yields from the data.

iii. *RNN*

The standard neural network model is given a new spin by the recurrent neural network. The input size of a vanilla neural network is constant, limiting its use to scenarios involving series input of unpredicted length. The judgments made by a recurrent neural network in the past are remembered and used to inform their present actions. They accept a vector of inputs and provide a vector of outputs [17].

$$it = \sigma(W_{xi} xt + W_{hi} ht - 1 + W_{ci} c_{t-1} + bi)$$
$$it = \sigma(W_{xi} xt + W_{hi} ht - 1 + W_{ci} c_{t-1} + bi) \quad (6)$$

$$ht = o_t \tanh(ct) ht = o_t \tanh(ct) \quad (7)$$

where tx, ot, and ht are the input, output, and state of the LSTM, respectively, for the data sample at time instance t; ct is the value of an LSTM cell reflecting encoded historical information gained from data samples taken before t; and σ(·) and tanh(•) are, respectively, sigmoid and tanh functions. Weights and bias are represented by other parameters [10, 18]. Prediction results in our study are obtained by first using the RNN to extract representative characteristics from inputs normalized temporal sequence data.

iv. *Proposed SLR Algorithm*

SLR, a hybrid method that combines SVM, LSTM, and RNN, is used. The SVM algorithm is utilized for Machine Learning, whereas the LSTM and RNN algorithms are used for Deep Learning. For jobs requiring the capturing of temporal dependencies, RNNs are utilized. RNNs remember each element of a sequence that has come before it in a hidden unit called a state vector and utilize this knowledge as they go through the input sequence one by one [19]. Despite the impressive predictive capability of RNNs, training them has proven to be very difficult owing to disappearing and expanding gradient difficulties. Long short-term memory (LSTM) cells, a kind of recurrent neuron specially developed to enhance RNNs, provide greater performance in many sequence modeling tasks. To avoid the vanishing gradient issue, LSTM cells use a unit of specialized called a memory cell to store inputs for a long period.

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Algorithm1: SLR

1. Begin
2. Calculate crop Yield as Production / Area/climate
3. Attributing Information to Soil Conditions
4. Assume Nothing Changes in Soil and Climate
5. Soil and climatic change should be included as a new column in the Data table.
6. Integrate the area-specific rainfall information.
7. To determine the impact of climate change on agricultural output, combine rainfall records with baseline information.
8. Initialize RNN at random points and set s, xt and Δ
9. for s = T, 1, -Δ do
10. if (s= =1) then
11. rain RNN for st = fw (s(t-1) ,xt)
12. else
13. train RNN for st=tan h (Ws S(t-1)+WxXt)
14. end if
15. return the best search agent X∗
16. end while
17. END

IV. RESULT AND DISCUSSION

The first step in this study's examination of the data was to categorize it according to its many features and types, such as crop type, yield, condition, and so on. All of the state-of-the-art methodologies, as well as the suggested approach, are put through their paces to make accurate predictions, and the outcomes of these analyses are shown below.

The dataset has a totalof 2200 entries where 1760 entries for training and 440 entries for testing purposes. Both training and testing data are been processed with all the existing and proposed algorithms.

Table III. Confusion matrix of each crop on proposed methodology on each crop individually

CROP	LABEL	TRUE POSITIVE	FALSE-NEGATIVE	TRUE NEGATIVE	FALSE POSITIVE
Rice	20	18	2	404	16
Maize	11	17	3	395	25
Chickpea	3	19	1	388	32
Kidney beans	9	16	4	411	9
Pigeon bean	18	12	8	402	18
Moth bean	13	14	6	408	12
Mung bean	14	18	2	399	21
Black gram	2	16	4	384	36
Lentil	10	13	7	366	54
Pomegranate	19	15	5	352	68
Banana	1	15	5	411	9
Mango	12	14	6	394	26
Grapes	7	18	2	388	32
Watermelon	21	17	3	406	14
Muskmelon	15	16	4	394	26
Apple	0	18	2	391	29
Orange	16	14	6	386	34
Papaya	17	17	3	382	38
Coconut	4	15	5	366	54
Cotton	6	16	4	400	20
Coffee	8	16	4	409	11
Jute	5	18	2	416	4

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The above table shows the confusion matrix parameter of the proposed method individually analyzed with the proposed methodology.

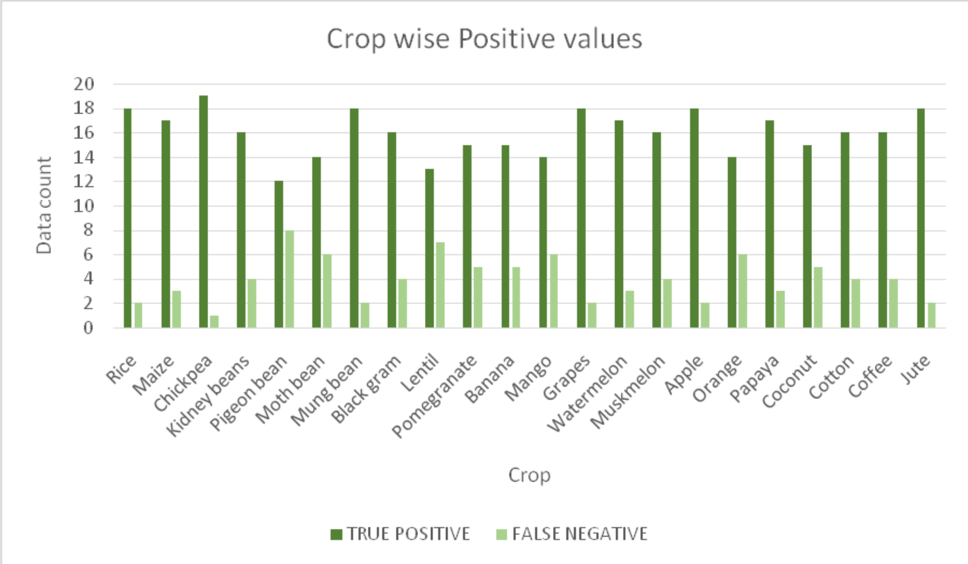

Figure 4. Comparison of positive values of different crop

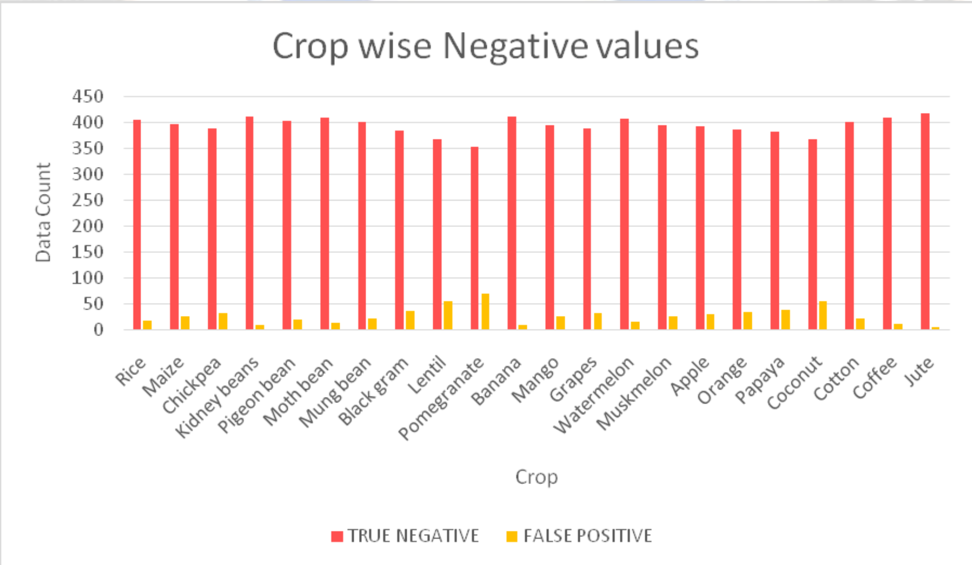

Figure 5. Comparison of negative values of different crop

The above figure 5 and 6 show true value comparison and false value comparison of the proposed methodology with different crops.

Table IV. Validation parameter of each crop based on the above confusion matrix.

CROP	PRECISION	RECALL	FSCORE	Accuracy	Specificity
Rice	52.94	90.00	66.67	95.91	96.19
Maize	40.48	85.00	54.84	93.64	94.05
Chickpea	37.25	95.00	53.52	92.50	92.38
Kidney beans	64.00	80.00	71.11	97.05	97.86
Pigeon bean	40.00	60.00	48.00	94.09	95.71
Moth bean	53.85	70.00	60.87	95.91	97.14
Mung bean	46.15	90.00	61.02	94.77	95.00
Black gram	30.77	80.00	44.44	90.91	91.43
Lentil	19.40	65.00	29.89	86.14	87.14

Pomegranate	18.07	75.00	29.13	83.41	83.81
Banana	62.50	75.00	68.18	96.82	97.86
Mango	35.00	70.00	46.67	92.73	93.81
Grapes	36.00	90.00	51.43	92.27	92.38
Watermelon	54.84	85.00	66.67	96.14	96.67
Muskmelon	38.10	80.00	51.61	93.18	93.81
Apple	38.30	90.00	53.73	92.95	93.10
Orange	29.17	70.00	41.18	90.91	91.90
Papaya	30.91	85.00	45.33	90.68	90.95
Coconut	21.74	75.00	33.71	86.59	87.14
Cotton	44.44	80.00	57.14	94.55	95.24
Coffee	59.26	80.00	68.09	96.59	97.38
Jute	81.82	90.00	85.71	98.64	99.05

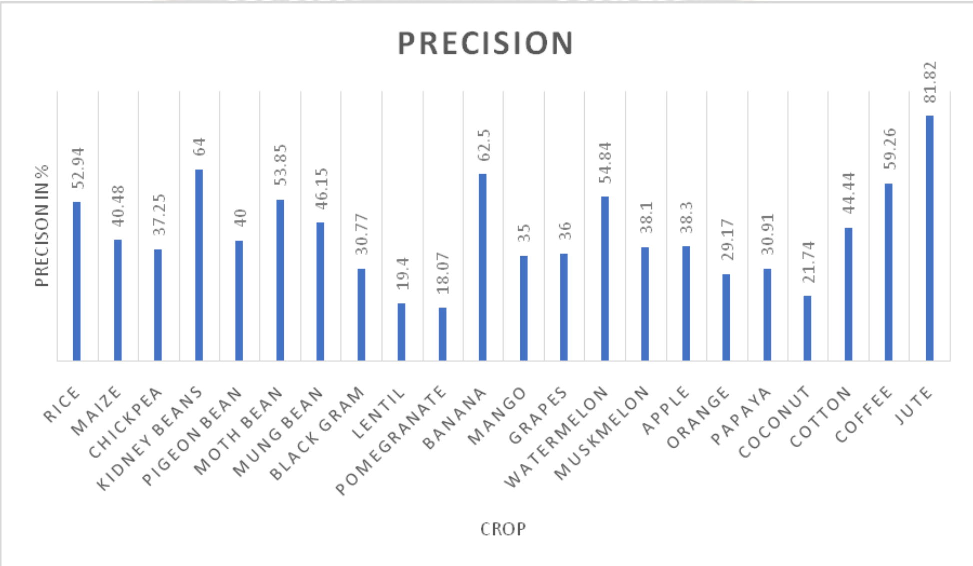

Figure 6. Comparison of Precision value of different crop

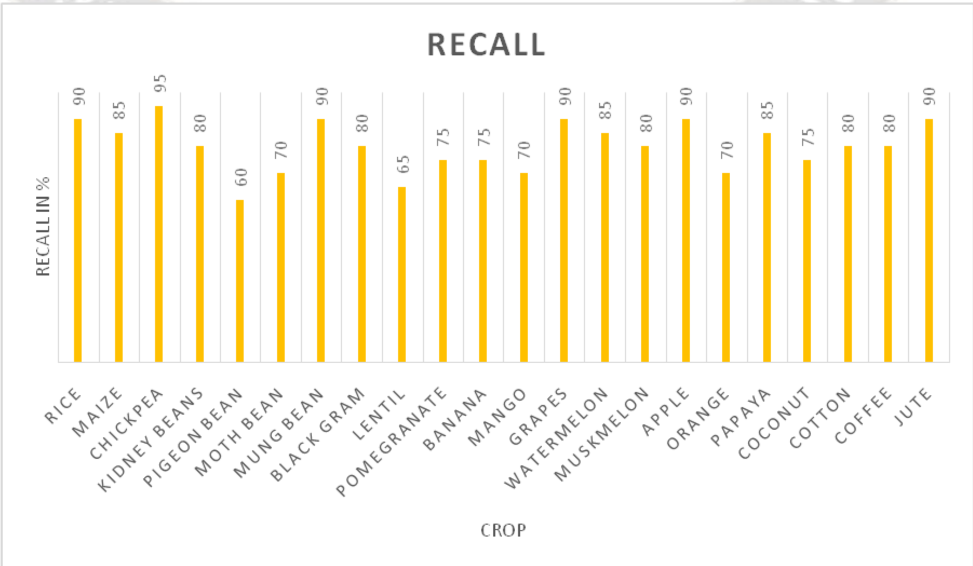

Figure 7. Comparison of Recall value of different crop

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Figure 8. Comparison of Fscore value of different crop

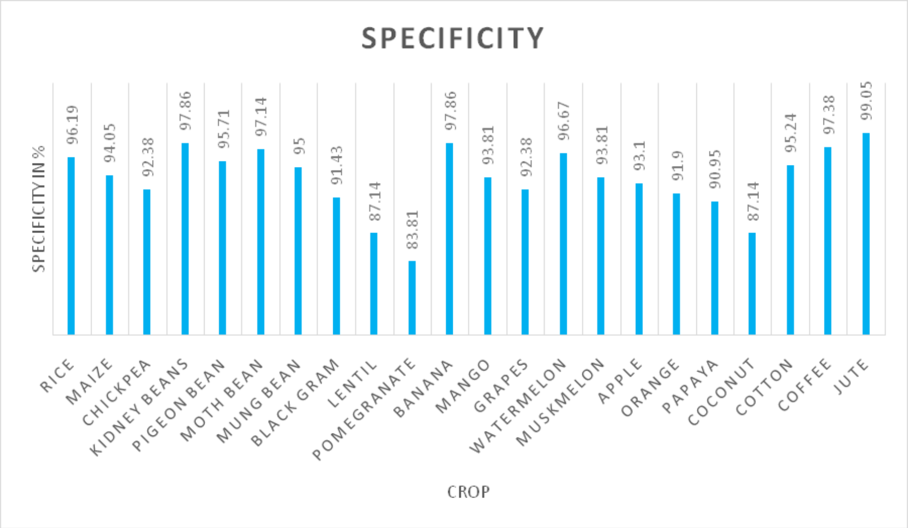

Figure 9. Comparison of Specificity value of different crop

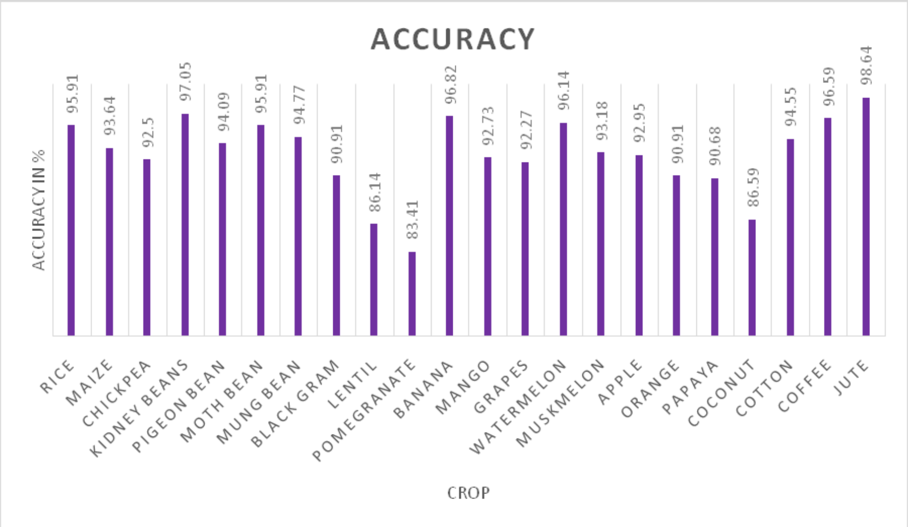

Figure 10. Comparison of Accuracy value of different crop

The above figures from 6 to 10 show precision, recall, accuracy, specificity, and sensitivity comparison of different crops with our proposed methodology.

$$Accuracy = (TP + TN) / (TP + FP + TN + FN)$$
$$Accuracy = (TP + TN) / (TP + FP + TN + FN)$$
(8)

$$Specificity/Precision = TP / (TP + FP)$$
$$Specificity/Precision = TP / (TP + FP)$$
(9)

$$Sensitivity/Recall = TP / (TP + FN)$$
$$Sensitivity/Recall = TP / (TP + FN)$$
(10)

Where TP can be defined as when the anticipated instances also turn out to be positive. FP occurs when expected positive outcomes turn out to be negative. The instances are TN when they are expected to be negative and turn out to be negative in practice. When situations are expected to be negative but turn out to be positive in practice, this is known as a false negative [7].

Table IV. Matrix of Average Confusion Comparison of the proposed algorithm's parameters to those of similar approaches

Algorithm	TP	FN	FP	TN
SVM	10.25	9.75	58.75	361.25
LSTM	12.50	7.50	49.88	370.12
RNN	14	6.00	41.88	378.12
SLR	16	4.00	26.73	393.27

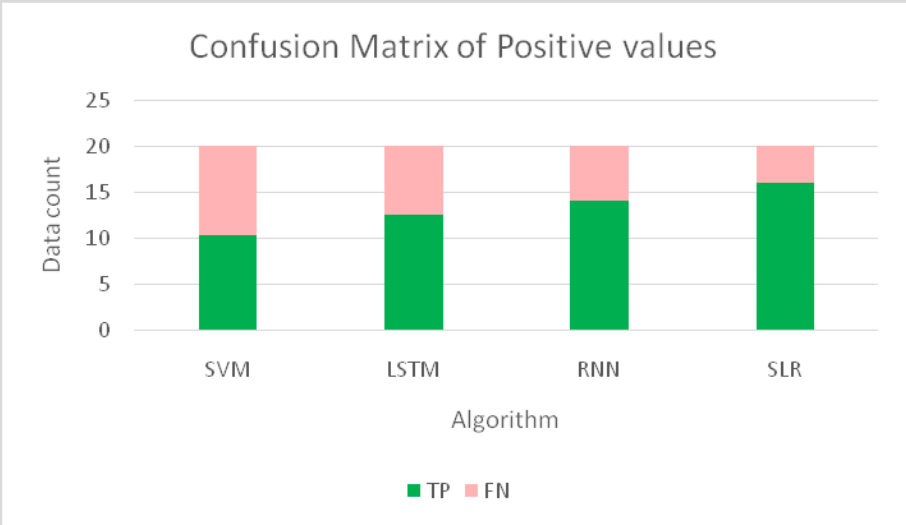

Figure 11. Comparison of confusion matrix of true values of different Algorithm

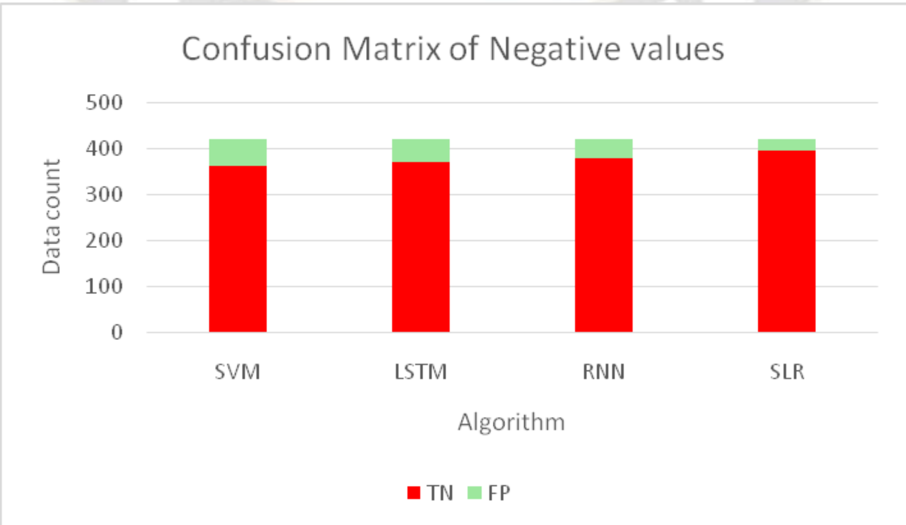

Figure 12. Comparison of confusion matrix of false values of different Algorithm

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Figure 11 and 12 shows a comparison of the average true and false values of the different existing algorithm in comparison with the proposed SLR algorithm.

TABLE V. Comparison of the Proposed Algorithm's Validation Parameters to Currently Used Methods

Algorithm	Precision	Recall	Fscore	Specificity
SVM	14.86	51.25	23.03	86.01
LSTM	20.04	62.50	30.35	88.12
RNN	25.05	70.00	36.90	90.03
SLR	**37.44**	**80.00**	**51.01**	**93.64**

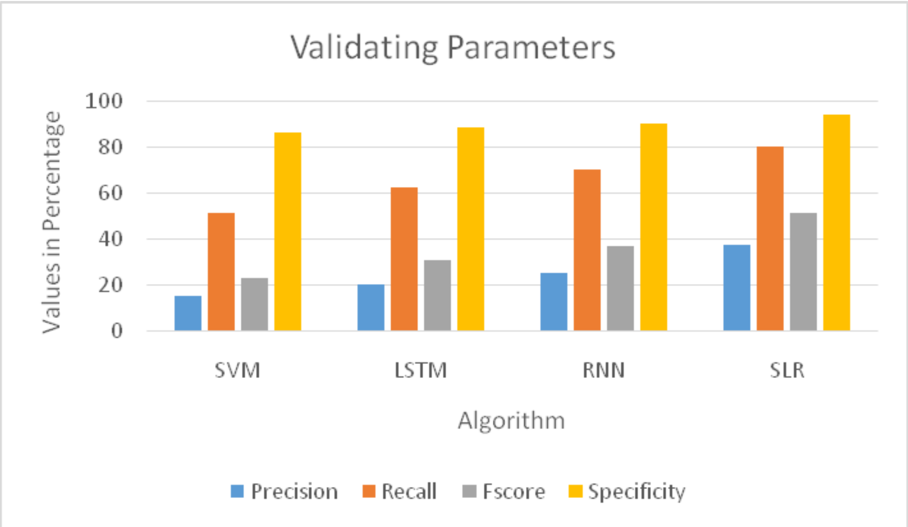

Figure 13. Examining the suggested algorithm's parameters against those of similar approaches

TABLE VI. Validity evaluation of new and established approaches

Algorithm	Accuracy
SVM	84.43
LSTM	86.96
RNN	89.12
SLR	93.02

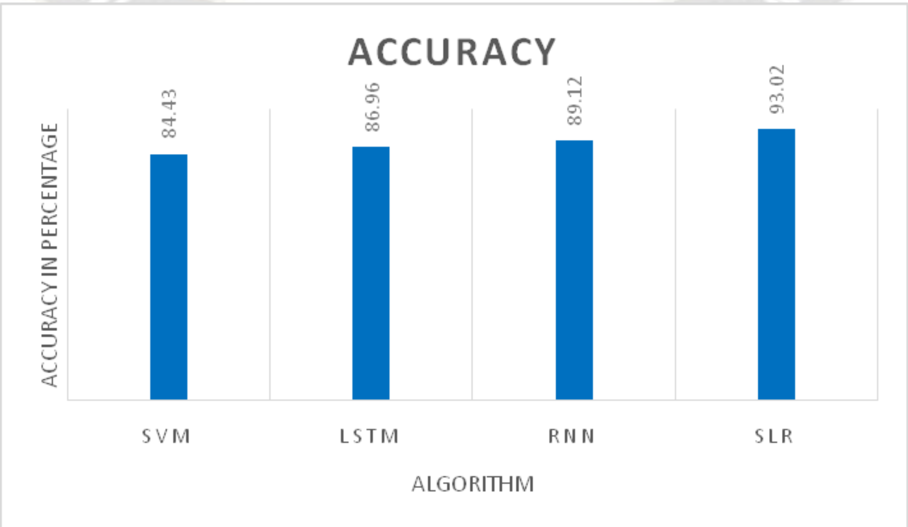

Figure 14. Evaluate the effectiveness of new and established approaches

Tables III, IV, and V, along with their corresponding Fig 5, 6, and 7, compare the proposed algorithm's Confusion Matrix parameters to those of existing methods, as well as its Validation Parameters to those of existing methods, and display a numerical and graphical comparison of the accuracy of the proposed algorithm and the existing methods. The suggested technique has the greatest value in accuracy, recall, F-score, and specificity, as demonstrated in all the graphs. It also has the lowest value in false positives and false negatives. When it comes to accuracy, the suggested SLR approach is superior to all others.

V. CONCLUSION

This study introduces a new hybrid approach for predicting agricultural yields using a state-by-state dataset of various crops. The suggested technique is a blend of support vector machines, long short-term memory, and recurrent neural networks, abbreviated as SLR. The database undergoes several preprocessing processes to normalize the data, and then the proposed and current techniques are trained and tested on the data. The suggested method has an accuracy of 93.02%.

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