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RESEARCH ARTICLE

Efficient prediction of recommended crop variety through soil nutrients using deep learning algorithm

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ABSTRACT

Agriculture and its related activities account for India's GDP to the tune of about 17%, in addition to that for 70% of the country's population, it is still the most popular occupation. Precision Agriculture, especially 'crop recommender systems,' is a paradigm that includes these strategies. In this research, crop recommended prediction is based on historical data that includes parameters such as phosphorus (P), soil nitrogen (N), temperature, humidity, potassium (K) content, rainfall, pH, and crop name. All of these data variables will be evaluated, and the data will be trained and tested to forecast crop production using the suggested Gated Recurrent Units (GRU) for developing a model. The GRU's test results are associated to those of the most regularly utilized deep learning approaches such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). With a validation accuracy of 0.9709 for 100 epoch, the GRU surpassed all other models. The results demonstrate that using the GRU model to analyze agricultural data enhances the model's performance by 0.98 in aspects of weighted accuracy. While comparing with LSTM model, CNN model came in second. As a result, the GRU model is exceptionally good at predicting the recommended crop at the conclusion.

Keywords: Deep learning, prediction, GRU, CNN, LSTM

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INTRODUCTION

Almost all ancient civilizations are built on the foundation of agriculture in order to ensure their existence. Agriculture has grown to be a $2.4 trillion worldwide business and it's a vital and important source of donor to emerging country prosperity. Agriculture, on the other hand, is prone to a variety of issues, the most of which are much unexpected in nature, such as a lack floods, blight, rain etc. These features, combined with unregulated use of chemical fertilizers and insecticides, as well as institutional factors such as insufficient government subsidies, a lack of corruption and credit, lead to the estrangement of farming community including an upsurge in debt, resulting in suicides and families burdened with additional responsibility. For the reasons stated above, Internet of Things and Artificial Intelligence must be introduced into the agricultural area in order to leverage statistical brilliance to give higher harvests at reduced prices (Singh and Singh, 2016). In this manner, this research work proposes a number of precision agricultural frameworks (Babu, 2013). Precision agriculture includes using technology to recommend

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fertilizers, agricultural practices, and crops to farmers, amid other things. Crop recommendation systems are a type of precision agriculture that picks crops based on certain criteria and data using a range of deep learning techniques. An accuracy related to an advice is determined by the type and quantity of data provided. These algorithms' statistical character can result in a large boost in yield. A high precision measurement is sought since the repercussions of failing to do so would be severe, including the waste of seeds, time, and a significant loss in production, amid other things. Temperature, soil qualities, humidity, and other predictors can all be utilized to make suggestions. Precision agriculture is not widely used in India, and farmers continue to rely on traditional crop-growing methods that provide low yields and are prone to failure, while ignoring a superior option of technology-based agriculture.

One of the methods of machine learning field is termed as Deep learning (DL). In the processes of harvesting and agricultural cultivation process, DL algorithms are employed in such activities to enhance the productivity, besides they are gaining popularity in the development of managerial and administrative work. The goal is in foddering vast ANN and enhancing high volumes of information, automatically excerpt characteristics from the outcomes and come to a conclusion depending on the information excerpts (Nguyen et al., 2019). The number of hidden layers present in a neural network is termed as "Deep". As network grows larger, model's performance increases. The food, national and global economies are affected due to the crop yields and its forecasts has a noteworthy yearly bearing on it. Crop output is heavily influenced by irrigation and meteorological data. Irrigation optimization and highly skilled irrigation procedures are critical since greater irrigation does not necessarily equal greater yield on different forms of irrigation. There are numerous types of irrigation and by forecasting the yield of the crops, the process and methods could be enhanced and augmented.

Katarya et al. (2020) discussed the Neural Networks Similarity-based Models, KNN, Ensemble-based Models and other techniques. Such algorithms examine a range of external elements such as temperature, meteorological data, and others like texture and soil profile in making the finest endorsements, not only do they boost yields, but they also save money and time. Mariappan et al. (2020) employed a machine learning technique to assist farmers in determining soil quality by analyzing several characteristics and recommending crops depending on the results. To boost the effectiveness of the Crop Recommendation System, the system employs the K-Nearest Neighbor Classification algorithm. To anticipate which crops are acceptable for the soil, the approach analyzes soil and crop data, as well as information on nutrients that are deficient in the soil for the specific crop.

To estimate fruit quantity and size, Apolo-Apolo et al. (2020) used an LSTM model with a Faster R-CNN model. The Standard Error (SE) between ocular fruit count and model fruit identification is 6.59 percent. The LSTM model is used to estimate total yield and per-tree yield, Maimaitijiang et al. (2020) used Partial Least Squares Regression (PLSR), Random Forest Regression (RFR), input-level feature fusion-based Deep Neural Network (DNN-F1), Support Vector Regression (SVR), and mid-level feature fusion-based Deep Neural Network (DNN-F2). Combining multimodal data improved yield forecast accuracy, according to the findings of Yang et al. (2019) who utilized low-altitude remote sensing photographs for constructing CNN architecture for projecting rice crop yield at the maturity stage. For RGB and multispectral image processing, the proposed model contains two separate branches. For the purpose of testing the model's capacity for the prediction of harvesting rice grain by utilizing 800 crop units, a 160-hectare area of land located in a Southern China which is an enormous region for growing rice is chosen. The network is tested against the classic vegetation index approach after being trained on multiple datasets. When it came to forecasting production of rice grain at maturity level, the VI-based regression model is outdone by CNNs trained with RGB and multispectral datasets as per the outcomes.

Chen et al. (2019) presented a faster Region-based CNN for the purpose of identifying and calculating the quantity of ripe strawberries, blooms, as well as immature strawberries. The model comprises of an average accuracy of 0.83 and 0.72 with respect to all identified things at a height of 2 meters and 3 metres respectively. Utilizing an SSD model with two lightweight backbones, MobileNetV2 and InceptionV3, an android app called as KiwiDetector was constructed by Zhou et al. (2020). To differentiate kiwis in the wild. The precise recognition rates for quantized MobileNetV2, InceptionV3, MobileNetV2, and quantized InceptionV3 are 89.7%, 87.6%, 90.8 %, and 72.8 percent correspondingly, as per the findings. To create an optimal DNN for agricultural production prediction, Kim et al. (2019) utilized augmented input variables from meteorological datasets and satellite products. The Cropland Data Layer (CDL), a high-resolution map for identifying plant types, is used as an input, along with hydrological, meteorological data and satellite-based vegetation indices. Using the Cropland Data Layer (CDL), a matching database is created and for identifying plant types, a high-resolution map is created. Alibabaei et al. (2021) described the ability of these models and their extensions, like Bidirectional GRU and Bidirectional LSTM, to forecast yields during the end of season. To estimate end-of-season production, the models incorporate past data like as irrigation timing, climatic data, and soil water content. At a location in Portugal, the implementation of this technology is evaluated for tomato and potato yields. With an R2 value of 0.97 to 0.99, the Bidirectional LSTM beat the other models. The findings suggest that studying agricultural data with the LSTM model increases the model's accuracy performance.

Sambasivan and Opiyo (2020) employed a CNN-based DL model in unbalanced datasets to identify disease in cassava crops. To boost picture contrast, the researchers employed a database of 10,000 labeled photographs that is preprocessed with a divergence limiting adaptive histogram equalization technique. Confusion matrix, sensitivity, precision measure, accuracy measure, and F1 score are the performance metrics utilized to assess the model. According to the authors, the best-case accuracy is 99.30 percent, while worst case accuracy is 76.9 percent. DL algorithms were used by Ramcharan et al. (2017) to identify illnesses in cassava plants. From a dataset of 11,670 images, the researchers employed Deep CNN to detect three diseases and two species of pests. In Tensor Flow, the authors used the Inception v3 algorithm, which is based on the GoogLeNet approach. The authors' efficiency ranged from 80 to 93.0 percent, and the results is verified using the confusion matrix.

DL techniques were used by Mohanty et al. (2016) to detect agricultural disease from a plant leaf picture collection. The researchers utilized a public database that included 54,306 images of dented and healthy plant leaves taken using a smartphone. These images is reduced to 256 × 256 pixels and given 38 distinct crop-disease pair class labels before being divided into three datasets: grayscale, color, and segmented. The dataset is then loaded into (AlexNet et al., 2012; Szegedy et al., 2015). Two of the most popular deep CNNs. The researchers attained a GoogLeNet accuracy of 99.34 percent and an AlexNet network accuracy of 85.53 percent. When utilizing the F1 score to validate the results, the authors obtained a mean F1 score of 0.9886 and 0.9848 for GoogLeNet and AlexNet correspondingly. To identify sickness in banana leaves, Amara et al. (2017) used a LeNet-based CNN architecture. For both RGB and grayscale images, the model is generated using digital libraries and data from open-source local that has been pre-processed then reduced to 60 x 60 pixels.

Hughes and Salathe (2016) used a newly built model to identify illnesses in a collection of photographs. In RGB images, the authors received the highest F1 score of 0.9971 in color images and a score of 0.976 in grayscale images. CNN is used by Ferreira et al. (2017) to identify weeds in soybean fields. The image collection for a soy plantation is taken with a phantom DJI3 drone at So José farm in Campo Grande, Brazil. The images are divided into square grids using the SLIC method. The segmented pictures are manually labeled to their class for training. AlexNet is used to classify the segmented picture dataset.

The AlexNet's performance is compared to those of SVM, AdaBoost, and RF. The AlexNet model is given a balanced dataset to measure its performance, and the authors claimed an overall accuracy rate of more than 90%, with 96.3 percent of photos appropriately categorized. For disease detection in maize leaves, Waheed et al. (2020) suggested a thick CNN that is 98.0 percent accurate and cost-effective (DenseNet). In simulations, the recommended model outdoes prior CNN models like NASNet, Xception- Net, EfficientNet, and VGG19Net in terms of parameters, less accuracy, computation complexity and computation time.

The organization of this paper is described as follows: Section 1 discusses on introduction in addition its associated work, Section 2 discusses the study proposed methods based on crop prediction, and the Section 3 discusses the result and discussion. Section 4 closes the report with a conclusion and recommendations for further research.

MATERIALS AND METHODS

Both environmental and soil characteristics were thoroughly considered in this study. The reason for this is that a certain type of soil will sustain a crop but the weather circumstances will not, resulting in a lower yield. This approach assists in making good agricultural expansion decisions. Our research aims to build and implement classification models from the accumulated soil nutrient dataset to classify recommend crop based on soil variety using a GRU model that mimics how humans acquire knowledge, train and evaluate them using various accuracy metrics in Python, and find the best fit model for our classification problem. Figure 1 depicts the proposed system's entire operation.

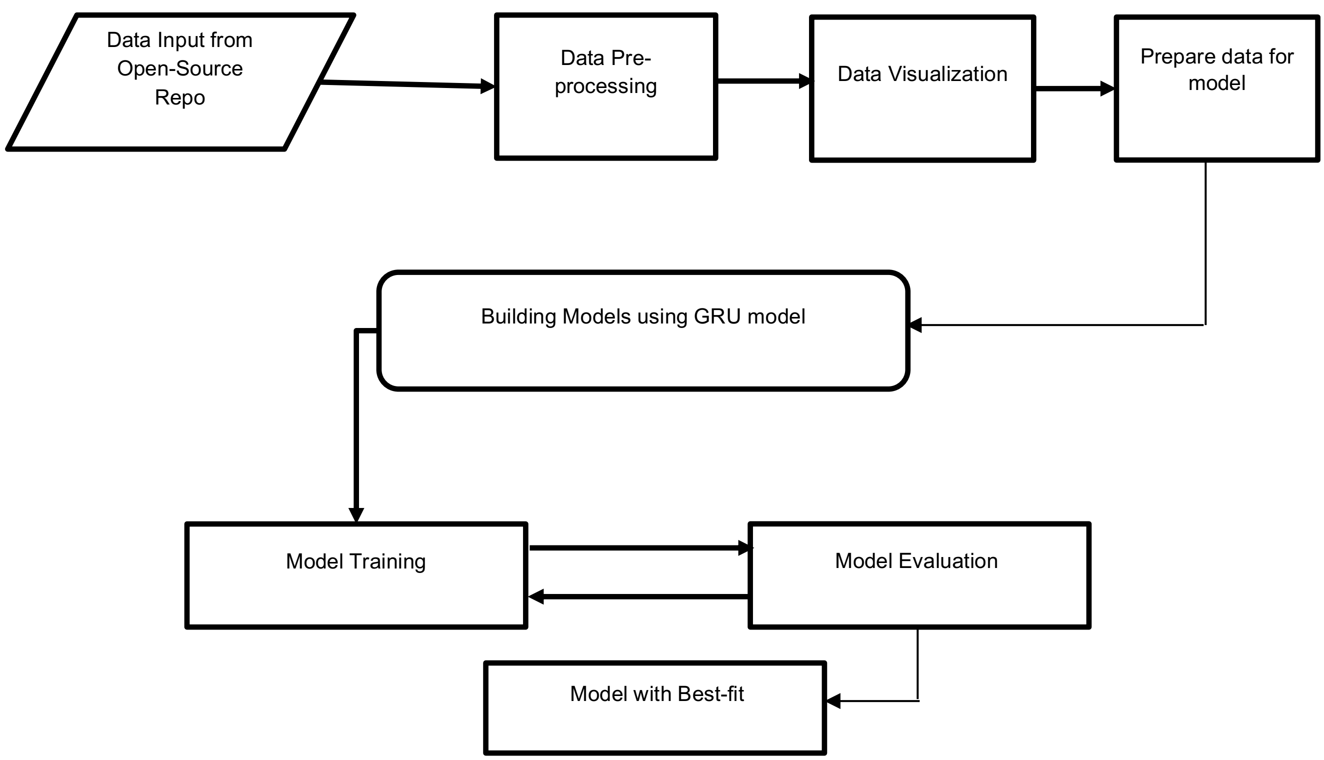

Figure 1: Proposed method architecture’s Block diagram

Data set description

This paper present with a dataset that will allow users to create a prediction model that will indicate the best crops to produce in a certain farm based on numerous criteria. The system is supplied with several datasets from Kaggle https://www.kaggle.com/notebook. Among the datasets are: i) Yield Dataset: This dataset comprises yields in kilograms per hectare for 22 different crops cultivated throughout all 50 states. ii) Soil nutrient content dataset: This dataset has three columns containing properties such as nitrogen, phosphorus, and potassium. iii) Dataset on the environment: Rainfall, temperature, humidity, and ph readings are all included in this dataset. Tables 1 and 2 show the first and second rows of a dataset used to forecast crop yield based on eight attributes.

Table1: First row for crop recommended dataset

First rows

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
5	69	37	42	23.058049	83.370118	7.073454	251.055000	rice
6	69	55	38	22.708838	82.639414	5.700806	271.324860	rice
7	94	53	40	20.277744	82.894086	5.718627	241.974195	rice
8	89	54	38	24.515881	83.535216	6.685346	230.446236	rice
9	68	58	38	23.223974	83.033227	6.336254	221.209196	rice

Table 2: Second row for crop recommended dataset

Last rows

	N	P	K	temperature	humidity	ph	rainfall	label
2190	103	40	30	27.309018	55.196224	6.348316	141.483164	coffee
2191	118	31	34	27.548230	62.881792	6.123796	181.417081	coffee
2192	106	21	35	25.627355	57.041511	7.428524	188.550654	coffee
2193	116	38	34	23.292503	50.045570	6.020947	183.468585	coffee
2194	97	35	26	24.914610	53.741447	6.334610	166.254931	coffee
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

Metadata

The number that will be utilized in the algorithm is prepared in all of the major data in the data set, which is the same as initializing all of the details. All of the crop names will be initialized with numbers in this information. This data allows us to quickly utilize the data in algorithm. Here you'll find all of the information on the crops, each with its own number. This number is unique, which means that one number is issued to one crop and the other crop is not given the same number. The dataset's metadata includes

2200 rows of data with 22 different types of crops, each with 100 rows of data, which is visualized using the Python tool Matplotlib.in figure. 2. Where the labels are placed evenly.

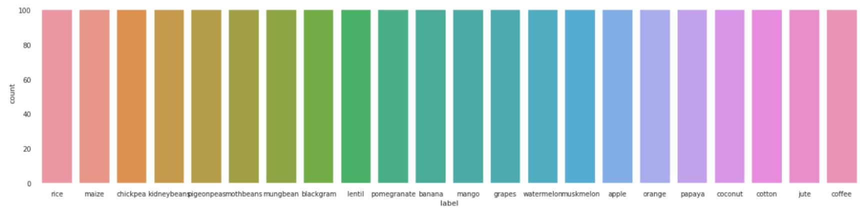

Figure 2: Data visualization for 22 kinds of crop

To produce the simulated results for the proposed study, the Python tool Matplotlib is utilized. In the acquired dataset, Figure 3 depicts the average value of each crop for N, K, P, rainfall, temperature, humidity, and PH. The nitrogen ratio in rice is 79.89.

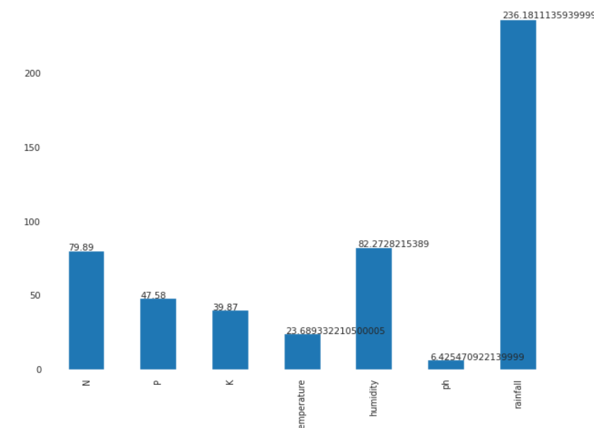

Figure 3: Histogram representing average value of crop

N, K, P, temperature, humidity, PH, and rainfall are the column names. Keras and TensorFlow is employed as back-end engines. As a result, we created a heatmap using a few data points from the dataset, as shown in Figure 4.

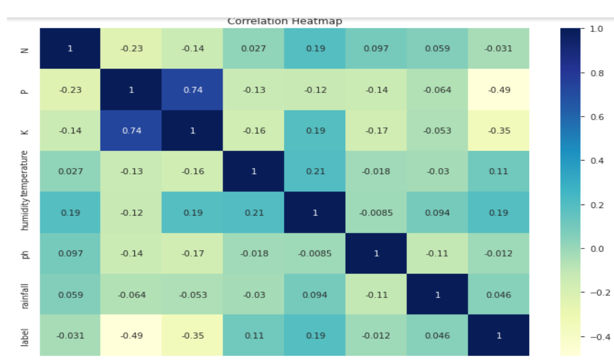

Figure 4: representation of correlation Heatmap

Data Pre-processing

Hear how raw crop data is cleaned and metadata is inserted by eliminating elements that are converted to integers. As a result, the data is simple to train. In this pre-processing, we first load the metadata into this, then connect the metadata to the data and replace the altered data with metadata. The data will then be sent again, with the superfluous items in the list deleted and the data separated into train and test data. We'll need to import train test split from scikit-learn to divide the data into train and test groups. This will help the pre-processed data separate into train and test categories depending on the weight supplied in the code.

Proposed Methodology Using GRU

The dataset is pre-processed and prepared for use in training the model utilizing it, and it is in CSV format. To begin, the dataset is divided into two sections: 25% for test data and 75% for training data. The GRU technique is used to turn the dataset into a model. GRU is a simpler variation of LSTM introduced by Chung et al. (2014) that requires less training time while improving network performance. A GRU cell performs the same duties as an LSTM cell, with the exception of a single hidden state that combines the forget gate and input gate into a single update gate. Furthermore, it merges the concealed and cell states into a single state, resulting in a GRU with half the number of gates as LSTM (update and reset gates).

As a result, it is a widely used and simplified LSTM cell. The following equation.1 is used to update the GRU cell's hidden state.

$$s_t = (1 - Z_t)\, s_{t-1}\, Z_t + \hat{S}_t \quad \text{……………………………………(1)}$$

The update gate, which governs how much of the GRU unit is updated, is calculated by equation 2 below.

$$Z_t = \sigma(W_z\, [s_{t-1}, x_t] + b_z \quad \text{………………………………………..(2)}$$

The reset gate is calculated in a similar way as the update gate, as shown in equation 3.

$$r_t = \sigma\, (W_r\, [s_{t-1}\, ,\, x_t\,] + b_r \quad \text{………………………………………...(3)}$$

The hyperbolic tan function is applied to the reset gate to produce a new remember gate, which is defined by the following function in equation 4.

$$\hat{S}_t = \tanh(W_s * [r_{t-1}\, ,\, x_t] + b_s) \quad \text{……………………………………(4)}$$

Update and reset are the two gates on the GRU unit. The update gate determines whether the previous hidden state should be disregarded or replaced with a new hidden state, whereas the rest gate determines if the previous hidden state should be replaced with a new hidden state. Z_t and r_t are their outputs, respectively. The bias vectors b z, b r, and b s are bias vectors, while the weight matrices W_z, W_r, and W_s are weight matrices. An adam optimization approach and binary cross entropy loss function are used to construct the model. The model is built and trained using the training dataset and the validation dataset. In subsequent to training the model, it is tested using the test dataset set. The steps for applying GRU to the dataset are as follows:

Step: 1 Divide the dataset for the train and test sets.

Step: 2 Construct a sequential model.

Step: 3 The model to be compiled

Step: 4 Final dense layer applying softmax as the activation function

Step: 5 Apply it on the train dataset (to evaluate the training performance, utilize the validation set).

Step: 6 Use the test dataset to evaluate the model.

Step: 7 Create a graph that compares training and validation/testing accuracy.

Step: 8 Create a confusion matrix by comparing the actual output to the projected result.

Using Adam optimizer and binary cross-entropy as a loss function, we compiled the model and find the accuracy of crop prediction. An algorithm is depicted for evaluation process of GRU model.

```
Load datset();

dataAugmentation();

SplitData();

loadModel();

for each epoch in epochNumber do

   for each batch in batchSize do

        y = model (attributes);

        loss = crossEntropy( Y, y) ;

        optimization (loss);

        accuracy (loss);

        bestaccuracy = max(bestaccuracy, accuracy);

return
```

All the hyper-parameters value are constituted in Table.3.

Table 3: Hyper parameter value of GRU model

Hyper-parameter	Value
Input layer	7
Hidden layer	50
Output layer	Softmax
Optimizer	adam
Loss	Categorized-cross entropy
Metrics	accuracy
Train_X	(1650,7,1)
Y_train	(1650,22)
Batch size	10
Epoch	100
Validation data	Test_X, Y-Test

RESULTS AND DISCUSSION

The implementation is carried out in Google Colab and is written in Python. The model is applied to 100 epochs using the training and validation datasets. Enhancing the collection of hyper parameters, like the amount of nodes in every layer, the amount of hidden layers, and the learning rate, is crucial for the best sequential prediction. Crop's class labels are likewise created and saved in the data target variable, which is also an ndarray. After that, the dataset is inserted into the data frame. There are two sections to the dataset: training and testing. When the suggested GRU model is used to the training and validation datasets, the training/testing accuracy and loss are displayed in Figures 5 and 6. When suggested GRU model is applied to 100 epochs of training data, the training accuracy is 0.9673 and the testing accuracy is 0.9709, whereas the training data for 100 epochs accuracy loss for training is 0.0874 and accuracy loss for testing is 0.0644.

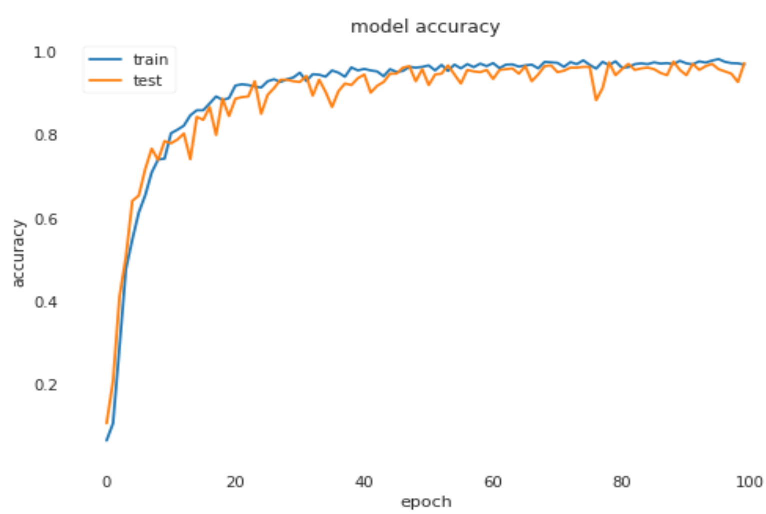

Figure 5: Training and testing accuracy of GRU model

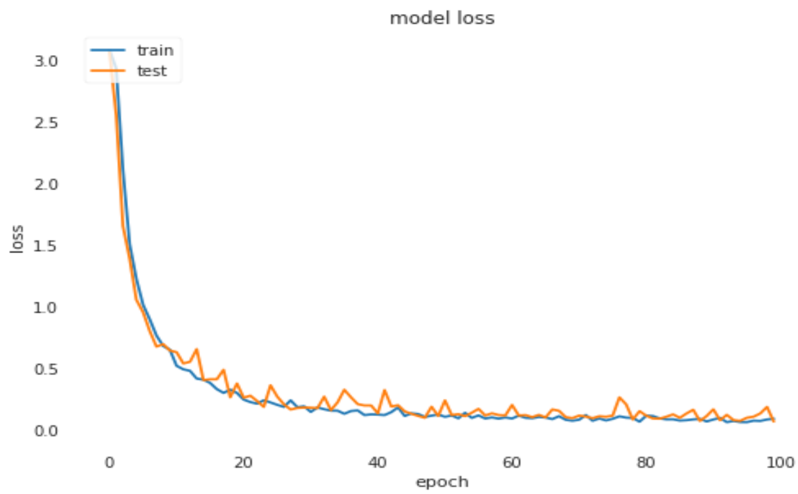

Figure 6: Training and testing loss of GRU model

Performance metrics for existing and proposed model

The GRU's performance in the test is compared to that the most popular deep learning methods, such as CNN and LSTM. Different models may be preferred for different crops, in terms of accuracy and precision for recommendation and classification. In a similar manner, we look at the performance of two commonly used crop prediction models. The test dataset is used to evaluate the model. Figures 7, 8, and 9 show the confusion matrix heatmap based on forecasting all 22 types of crop for suggested GRU, LSTM, and CNN. The following is the outcome of creating a crop prediction for training and validation.

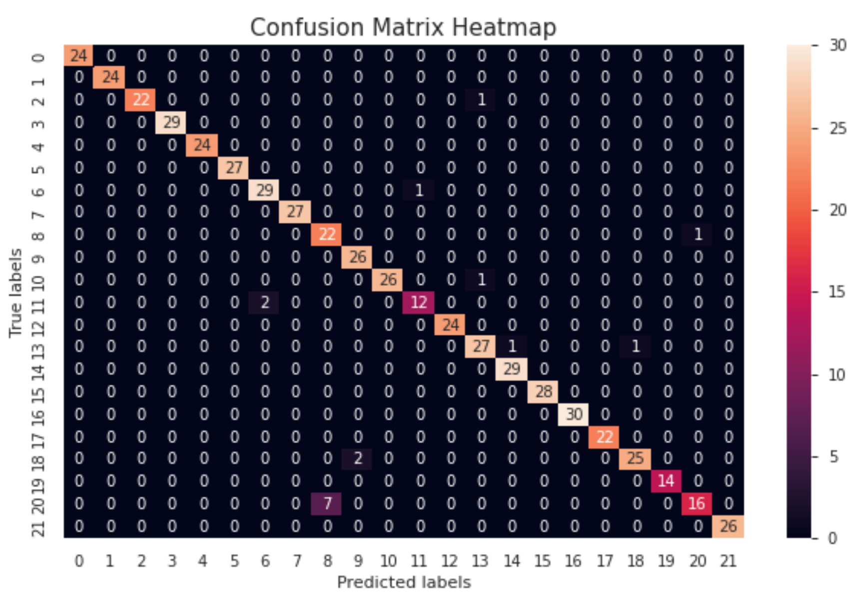

Figure 7: Confusion matrix heatmap for proposed GRU

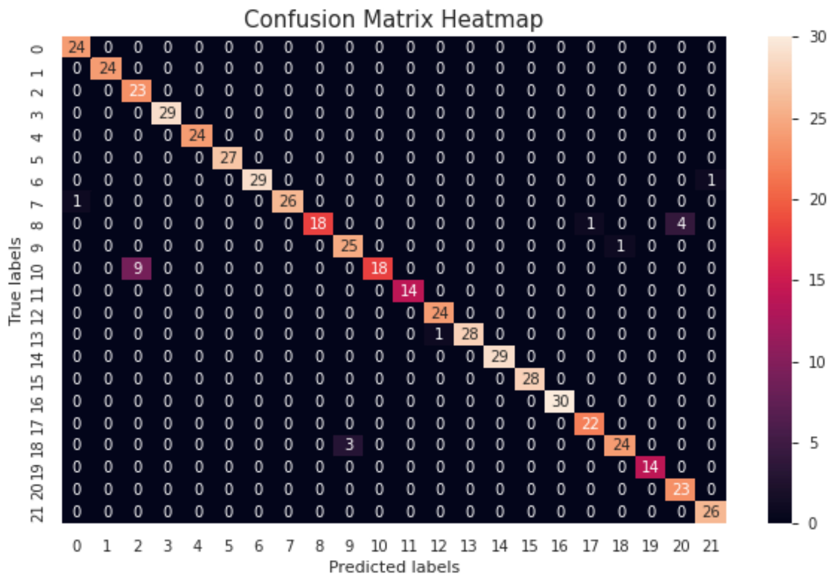

Figure 8: Confusion matrix heatmap for LSTM

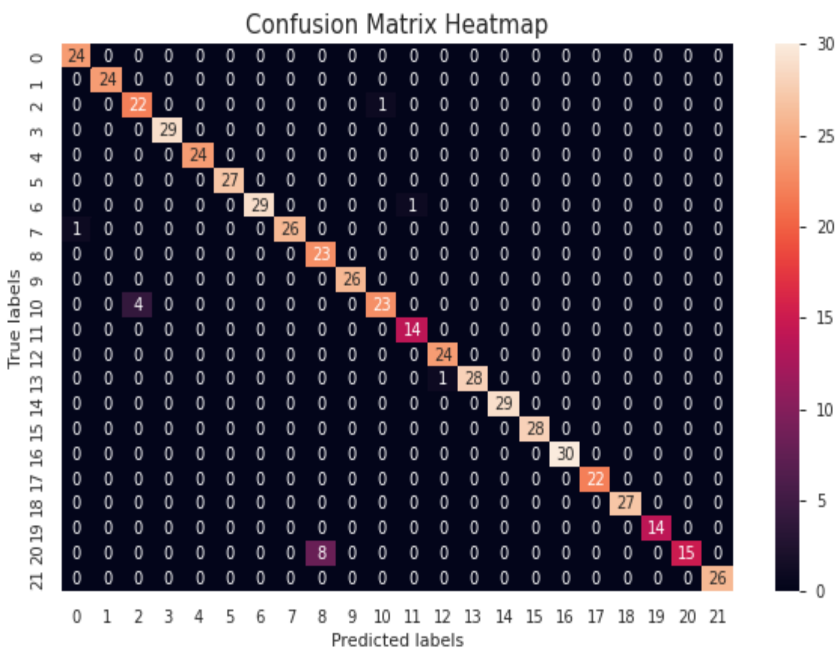

Figure 9: Confusion matrix heatmap for CNN

Table 4 and Figure 10 show the accuracy, precision, recall, and f1-score of deep learning models. The ratio of true positives to total positive class instances predicted by the model is known as precision. True positives and false positives are both included in the positive class instances. The model's accuracy may be measured by the number of false positives it predicts. Positive Predictive Value (PPV) is another name for it. The number of true positives divided by the number of false negatives is the ratio of true positives to false negatives. As a result of the high recall, there are fewer false negatives. It's also known as sensitivity or true positive rate. The F1 score, often known as the F1 measure, is a test accuracy metric that finds a compromise between recall and precision. When computing the score, accuracy and recall values are taken into account. The best-case scenario is when the F1 score hits 1, whereas the worst-case scenario is when it approaches 0. It's typically employed when the dataset contains a lot of output classes that are severely skewed. A false negative, on the other hand, occurs when a model wrongly forecasts a positive class as a negative class. A false positive occurs while a model incorrectly forecasts a negative class as a positive class.

Table 4: Performance metrics for deep learning algorithms for predicted crop

Model	Accuracy	Precision	Recall	F1-Measure or F1 Score
Proposed GRU	0.98	0.97	0.97	0.97
LSTM	0.96	0.97	0.96	0.96
CNN	0.97	0.97	0.97	0.97

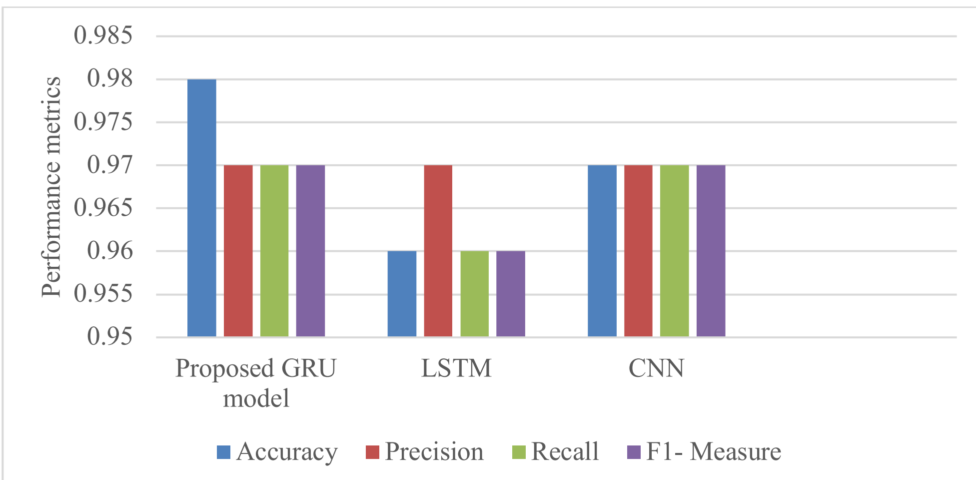

Figure 10: Comparison of deep learning models based on performance metrics

On the basis of the testing data, the suggested GRU model has a precision of 0.98. When recall, precision, and f1-score are utilized to compare the performance of LSTM and CNN in forecasting the crop, the recommended GRU model appears to be the best supporting approach since it has the highest precision value and accuracy.

CONCLUSION

For agricultural datasets, the proposed GRU model is shown to give the greatest accuracy and precision when compared to LSTM and CNN, among other deep learning algorithms. As a result, in the proposed system, the GRU algorithm is employed to discover the appropriate crop list. The current Crop Recommendation System employs a machine learning algorithm that takes into account a few variables such as temperature, rainfall, and moisture. However, the Proposed System employs the GRU algorithm with the inclusion of all main crop nutrients such as phosphorous, nitrogen, potassium, and pH, which aids in the identification of more suited crops for the soil with greater accuracy than the present system. According to a review of the crop prediction system's classification report, the suggested GRU provides superior accuracy for production rate than the CNN algorithms and LST. The GRU algorithm’s accuracy is 98 percent, the LSTM algorithm is 97 percent, and the CNN algorithm is 97 percent. The accuracy is determined by combining the results of the training and test data. The dataset is then fitted into the model for estimate purposes. The accuracy of the system derived from classification report is determined using the recall, precision, and f1 factors. The suggested GRU algorithm for classification in deep learning method is chosen to create the Crop prediction system since it produces greater validation accuracy. The collected results will assist farmers in determining the crop yield so that they may select a better crop with a higher yield and apply only the quantity of fertilizer necessary for that land. This manner, we can assist farmers in growing crops that provide a higher yield. We intend to create a web framework using Python Flask in the future, as well as expand the dataset with other crops and internal features such as crop fertility.

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