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An IOT based Solution for Crop prediction based on Novel Hybrid Deep Learning Techniques

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***Abstract*—Agriculture is one of the most significant economic sectors in every country. Smart agriculture aims to accomplish exact management of irrigation, fertiliser, disease, and insect prevention in crop farming. In the agricultural area, wireless sensor networks (WSNs) are used to gather data and communicate it to servers over a wirelesslink. This work presents a multiclass model based on a hybrid deep learning classifier approach (CNN + LSTM). Eighteen input characteristics were utilised to create the model, and crop yield was found and organised into three key components. When creating the multiclass model, the relative significance of the components is taken into account. For categorization of 3 crops: rice, groundnut and sugarcane, an objective function is defined. Furthermore, data visualisation analysis is utilised to identify essential approaches in progress of smart agriculture that may efficiently increase efficacy of production and assure agricultural product quality. Smart agriculture is progressively being incorporated into agricultural production, and advent of the Internet of Things (IoT) is giving it a technological boost. Agricultural tasks may be precisely accomplished using the IoT' detecting, ID, transmission, observing, and input capacities, which saves farmers' time and enhances crop yields and advantages them in long run. We installed Smart Agriculture IoT equipment in the farm for monitoring reasons and used the algorithm in our research to do an actual-scenario analysis; the findings show that this suggested scheme is actually practical. The categorization findings are compared to the results acquired from on-the-ground agricultural specialists.**

***Index Terms*— data visualization analysis, deep learning classifier, hybrid classification, smart farming.**

I. INTRODUCTION

For individuals in India, agriculture is a primary source of income, and it is essential to the development of the regional livelihoods. Despite the widespread use of information technology in other sectors of society, such as manufacturing, pollution monitoring, and other areas of life, conventional agriculture production is still mostly reliant on manual labour [1]. The extensive use of wireless sensor networks (WSNs) in agriculture is evidenced by the fact that they are useful in monitoring soil information in appropriate locations and supporting its use of conventional irrigation systems, among other things. This technology has the potential to improve irrigation practises and make agriculture more intelligent [2] by collecting data throughout the agricultural production system [1].

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WSNs are critical in the notion of smart agriculture since they monitor and gather interest data in agricultural fields for use in numerous applications. Smart agriculture takes significant efforts to realise precision irrigation, fertilisers, and pesticides based on the crop development model and WSNs in agriculture to reduce water waste, low soil fertility, fertiliser abuse, and illnesses. WSN sensor nodes in fields can wirelessly communicate collected soil data to the sinknode [3]. In [4], the authors use WSNs to collect data on temperature, humidity, soil moisture content, and wind speed.
Because of mediators' lack of knowledge about crop production and yield, the farmers who laboured during the full growing season get paid less (agents for bargaining). Farmers' hard labour would not be in useless if they were given proper instruction or supportin crop cultivation, yield pricing, and crop selling. If not, crop output will be diminished, affecting the country's economy. As a result, if the government provides appropriate support for these abilities in addition to the conventional manner of conducting agricultural, the country's economy will considerably improve [5].

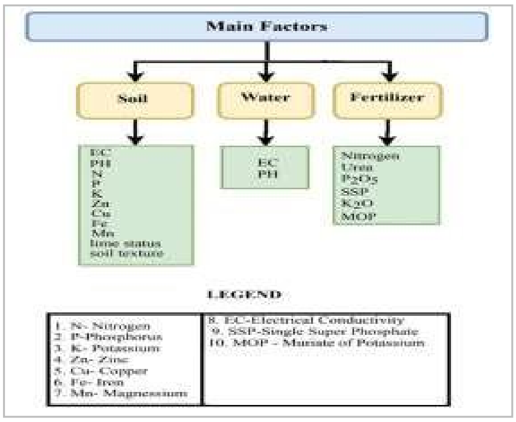

Fig 1. Primary factors and comparing sub-factorsdistinguished for the multiclass model

This research suggests using Intelligent Agriculture to analyse farm data. The following are some of the characteristics of our Intelligent Agriculture platform:
(1) IoT sensors for temperature, humidity, illumination, atmospheric pressure, irrigation and electrical conductivity of soil, with data sent to the platform every 10 minutes by the system; (2) A Python-based online application that aids in the collection of data from IoT devices. The suggested Intelligent Agriculture system makes use of inexpensive sensors, which makes Intelligent Agriculture systems more popular. This study analyses the data collected from the Intelligent Agriculture system and also makes use of publicly accessible datasets. The analysis' objectives include examining a farm's environmental conditions and selecting appropriate crops for development. Furthermore, the study examines farm environmental aspects to better understand how weather conditions affect environmental changes and identifies which crops are appropriate for the farm depending on time sequence. For creation of the multiclass model, data on the chosen primary components, namely soil, water, and fertiliser were collected for multiple crops from three different regions of Maharashtra, India.
The following principles are included in our suggesteddata analysis approach: (1) IoT sensors are used to collect data from farm fields. (2) Using WSN, data may be sent from a farm field to a device. (3) data collection and standardisation; (4) data analysis to examine the relationship between various environmental factors and, as a result, the farmers' rules of thumb; (5) determining if a chose crop has been planted in the proper soil; and (6) setting a basic worth in cluster dependent on future conditions and exhorting on whether a harvest is appropriate for farm
(7) The hybrid multiclass classifier system is compared to the outcomes of other traditional classifiers including Nave Bayes, Random Forest, and SVM. The proposed data analysis technique has been put to the test, and it has helped determine if locally grown crop is a good fit. The suggested method is feasible, and helps farmers comprehend their farm'senvironmental indices, according to results of theexperiments.
IoT devices can measure air temperature,atmospheric pressure, humidity, soil moisture content,illumination, and soil electrical conductivity. Sensorswill be used to assess soil macronutrients such asnitrogen, phosphorus, and

potassium, as well as other soil parameters such as moisture, pH, and temperature. Organisation of paper as section 1 gives introductionabout smart agriculture, section 2 presents literaturereview, section 3 depicts the proposed system model,Section 4 discusses result and discussion, section 5concludes the paper.

II. LITERATURE REVIEW

Foreign developed nations began collecting agricultural data earlier, and their study and implementation of intelligent agriculture is more advanced. The agricultural environment monitoringservice system was conceived and constructed by Jeonghwan Hwang et al. [9]. The system collected photos of soil and crops using wireless sensor technology and GPS positioning technology, allowingfor remote crop monitoring and crop management, as well as the utilisation of solar power to assure the equipment's proper operation. The Climate Corporation used climate, geographic location, and other factors to give natural catastrophe insurance to farmers, ensuring that agricultural production was protected to some extent [10].
Various sensors are used to measure soil factors including as temperature, pH, light, humidity, and moisture [8]. Utilizing an Analog to Digital Converter,the values are converted to digital and serially transferred to cloud using a Raspberry Pi. Outcome is shown on a laptop or through a mobile app. With the use of IoT, the system monitors the entire soil parameters. Soil factors such as pH, soil moisture, humidity, and temperature are continually monitored utilizing sensors in order to ensure effective crop yield.The creation of an optical transducer [11] is used to construct a system in which soil fertility is improved and soil quality is improved. Low, medium, and high levels of NPK are achieved. The data is collected usingan Arduino microcontroller, and the analogue output is transformed to digital.
People are presented with a greater data system asinformation advances that has drew the attention of domestic and foreign academics that specialise inagricultural data analysis. Lamehari et al. fostered therural construction by examining farming ecological information [13] that help makers and middle person organizations in settling on better choices, smoothing out the dynamic interaction, and accomplishing the objective of expanded horticultural usefulness andlogical normal asset the executives. Gabriel, andcolleagues created and implemented a system formonitoring soil and analysing soil fertility, as well asgiving farmers with actionable advice for soil improvement. Li Xiufeng et al. proposed a visual intuitive framework that could convey networkinformation administrations to clients and makeinformation examination more straightforward [14]. Kursa et al. [11] used Boruta, an all-relevant featureselection approach that aggregates all features that arecrucial to the result in certain situations. Most classicfeature selection algorithms, on the other hand, use a minimally optimum strategy in which they rely on alimited group of characteristics that produce the least amount of error on a chosen classifier. MarcanoCedeno et al. [12] suggested a component choiceprocedure dependent on consecutive forward choice utilizing a feed forward neural organization to decide forecast mistake as choice models.
Sensor technology, Quick Response (QR) Codetechnology, RFID technology, and embedded system technology have all been created for the practical implementation of the Internet of Things. The use of sensors is one of them. It is a type of sensing device that can detect information from objects and convert itinto signals or other forms for output based on particular criteria, in order to meet informationtransmission, recording, processing, and control needs[15].

III. PROPOSED METHODOLOGY

A. System Architecture

In the realm of smart agriculture, the implementation of Internet of Things (IoT) technology results in improved agricultural production management, environmental monitoring of production and aquaculture, and control of the quality and safety of agricultural products and feed. It has the ability to detect problems and provide a management platform for agricultural production, animal husbandry, and aquaculture at crucial locations, thereby ensuring the quality of agricultural products. The proposed design for a smart agricultural Internet of Things system is depicted in Diagram 2.

B. Components used in proposed system

The device monitors the farm and gives the farmer several forms of information about the present condition based on the readings of various sensors such as temperature, humidity, soil moisture, UV, IR, and soil nutrients. Farmers' can take quick action which will help them in increasing the farming production and make the most use of natural resources, making their product (crop yield) ecologically friendly. By appropriately

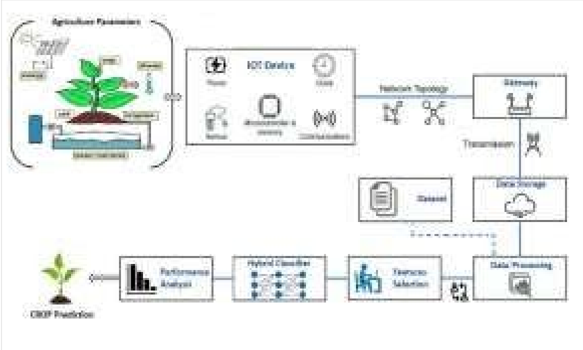

Fig 2. The proposed architecture of a smartagricultural IOT system

monitoring the many current conditions, our proposed system will boost the amount and quality of the crops. It's an IoT device that uses the “Plug and Sense” principle. Laptops and smart phones can display real-time data for several factors. Following are several important sensors details which are used to get live farm reading. Figure 3 shows the organisationof various sensors to andrino device and laptop / computer to get live farm reading.

Soil moisture sensor

The soil moisture sensor is used to determine thevolumetric water content of soil. On basis of which soilmoisture is measured, parameters such as electrical resistance and dielectric constant are determined. Two probes are included in the soil moisture sensor. These probes are inserted into the soil to acquire the moisturevalue. Farmers may use the data generated from sensoras a support system to better manage their irrigation system.

Soil temperature sensor

The soil temperature sensor is used to determine the temperature of the soil. Thermocouples and thermistors are used in a variety of designs for these sensors. The functioning base of the sensor is revealed by the voltage measurement across the diode. Electrical signals are transmitted by the sensors, which are translated into other units of measurement such as Kelvin, Celsius, and Fahrenheit. The voltage differences are amplified, and the gadget generates ananalogue signal that is proportional to temperature.

Soil pH sensor

The pH of soil dictates whether it is acidic or basic. The availability of nutrients and microbes is influencedby the pH of the soil. The pH scale ranges from 0 to 14, with 7 indicating neutrality. Severe acidity is indicated by a pH less than 5.5, moderate acidity by a pH less than 6.5, neutrality by a pH between 6.5 and 7.5, alkalinity by a pH above 7.5, and strong alkalinityby a pH over 8.5.

Fig. 3 working model of IOT sensors for SmartAgriculture

C. System Module

Following are several important modules which are used during the execution of proposed work for crop prediction.

Data Cleaning and Normalization

Data cleansing and normalisation are the initial steps in data analysis. For IoT data transfer, our system leverages 4G networks, which assures consistent network quality. The data is cleaned first; as farm environments often change in a linear rise or decline pattern, it seldom fluctuates dramatically. Normalization rescales a dataset so that each value falls between 0 and 1. It uses the following formula todo so:

$x_{new} = (x_i - x_{min}) / (x_{max} - x_{min})$

where:

x_i: The ith value in the dataset

x_{min}: The minimum value in the dataset x_{max}: The maximum value in the dataset

Features Selection

After performing the pre-processing important featuresare selected from the dataset. Given that the decision tree model, it divides the sample data by selecting the best features from all of the features. It has been used in the decision tree classifier to determine theimportance of attributes by calculating their value of information gain, their information gain ratio, their Gini index, and other metrics. With the help of the tree model, the feature selection process can draw specific higher-importance features [7], which will aid in the selection of significant characteristics from among the many other opportunities available. In recent years, integrated woodlands including such random forest and generalised backward differentiation and training (GBDT) have emerged, partially overcoming the problem of decision tree overfitting. A random forest-based feature selection method is used as a result in this system as part of its feature selection. The following is the formula for calculating the model:

By employing the convenient sampling of returning, the random forest produces the sub-data collection that is then used to form the decision tree model, which is then used to predict the future. As a consequence, some data will be missed out on throughout the sampling procedure as a result. It is necessary to evaluate the out- of-bag calculating the associated error, which is saved as OOB error1. The newly built decision tree model can be utilized to do so.

(a) Select all of the data that corresponds to one of thefeatures from the data that was taken just outside of the bag, and then randomly adjust the value of a portion of the data, i.e., introduce some noise tothe system to cause interference.

(b) Suppose the number of selected trees in the random forest is n. For each decision tree model, calculate OOB error1 prior to actually addingnoise and OOB error2 after introducing noise interference before and after introducing noiseinterference

(c) Calculate the significance of features based on theinaccuracy in the formula error

$$\frac{1}{n}\sum_{i=1}^{n}(OOB\_error1_i - OOB\_error2_i)$$

It is logical to assume that the more essential thecharacteristic, the worse the prediction impact after noise is. As a result, the formula may be used to determine that the higher the value, the more importantthe trait is.

(d) Repeat steps (a), (b), and (c) for each characteristic to arrive at a calculation of its relevance.

(e) Feature filtering is carried out using the computed feature significance. After sorting all of the qualities, choose the most important ones using one oftwo methods: selecting a specific number of features or creating a feature priority threshold.

Figure 4 shows the features with their features importance value in descending order. Cu has thehighest features importance while the pH has the lowest feature importance among all.

Cu	0.164475
P	0.154644
Mn	0.147950
EC	0.134915
S	0.128977
N	0.091529
B	0.049403
Zn	0.047928
Fe	0.037074
K	0.022646
OC	0.014967
pH	0.005491

Figure.4 Feature Importance Calculation

Machine Learning Classification

To extract and identify essential information from massive data, data mining and machine learning techniques are utilised. To our knowledge, the majorityof existing works that recognise sardonic text employ Naive Bayes or Support Vector Machine. Random Forest and Weighted Ensemble are two alternative methods to this problem that we offer.

a) Random Forest (RF):

RF is a supervised learning approach that uses smaller portions of the training dataset to generate multiple decision trees. The output class is the mode or mean average of each output class [8].

b) Naive Bayes (NB):

Based on Bayes' theory, NB classifiers are probabilistic in nature. This classifier assumes that classes are conditionally independent. It is assumed bythe NB classifier that the existence or absence of a class characteristic (feature) is unrelated to other features. The formula for determining the odds of a positive or negative output is

$$P(s|E) = \frac{P(s) * P(E|s)}{P(E)}$$

Where s stands for predicted class output, and E standsfor test data, the class of which is being predicted. P(s)and P(E|s) are gained throughout training. The NB classifier uses less training data to calculate the mean and variance of the variables necessary forclassification. [16].

c) SVM:

SVM is a pattern recognition machine learning approach for regression and classification. A collectionof training dataset is assigned to another one of n classes. SVM learning creates a model that categorisesnew data. The SVM supervised learning model represents samples as dimensions of space. These locations are mapped so that samples from different classes are further apart. New samples are translated into the very same space and assigned to classes based on their position. SVMs can classify non-linearly as well as linearly. The kernel technique to non-linear classification involves transforming signals towards large number of features spaces. To use the higher dimensional space with the maximum distance towards the training sample data point improves separation [17].

Hybrid Deep Learning Classifier (CNN + LSTM): CNN is a popular tool in classification techniquesbecause it has the quality of concentrating on one ofthe most obvious objects inside the line of sight, whichis particularly useful. This technique is widely applied in time series analysis since it has the virtue of growing in proportion towards the succession of time data. Based on the characteristics of CNN and LSTM, a forecasting model which is based on CNN-LSTM isdesigned and tested. The model's essential structure iscomprised of CNN and LSTM layers, each of whichhas an input layer, a 1D convolution layer, and apooling layer.

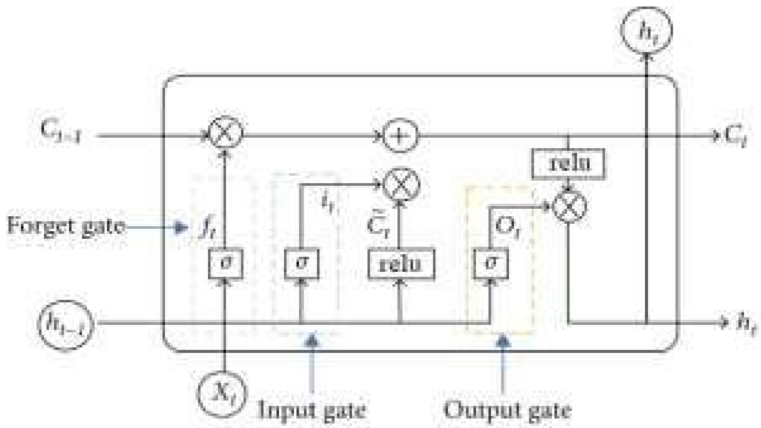

Fig 5. LSTM hidden layer, and complete connectionlayer

Algorithm

(1) Input: Farm dataset with multiple features is given as input to the CNN-LSTM model.

(2) Data Normalisation: As there is a wide gap in the input dataset, the data normalisation technique is used to normalise the data in order to improve the train the model output, following formula is used for data normalisation:

$$y_i = \frac{x_i - \overline{x}}{s},$$

$$x_i = y_i * s + \overline{x},$$

where yi is the normalise value, xi is the input data from dataset, x bar is the average of the input data, and *s* be the standard deviation of the input data.

(1) Initialization of network: initialize the weights andbiases of each layer of the CNN-LSTM.

(2) CNN layer calculation: The input data is sequentially processed through the CNN layer'sconvolution layer and pooling layer, the input data is feature extracted, and the output value is obtained.

(3) LSTM layer calculation: the output data of the CNN layer are calculated through the LSTM layer, andthe output value is obtained.

(4) Output layer calculation: the output value of the LSTM layer is input into the full connection layer to get the output value.

(5) Calculation error: The related error is derived by comparing the output value calculated by the output layer with the real value of this set of data.

(6) To determine if the end condition has been reached,a predetermined number of cycles must be performed,the weight must be below a specific threshold, and theforecasting error rate must be below a specified threshold. The training will be completed, the CNN- LSTM network will be updated, and step 10 will be executed if one of the end conditions is met; otherwise,step 9 will be performed.

(7) Error backpropagation: Continue to train the network by propagating the estimated error in the opposite direction, updating the weight and bias of each layer, and returning to step 4. (10) Save the model: Save the trained model for new data cropprediction.

(11) Output result: To finish the forecasting procedure,output the repaired results.

Figure 6 shows the CNN + LSTM model which is used for training and testing purpose for crop prediction. It includes several layers namely convolution, max pooling, flatten, dense and dropout. Additionally, it used two LSTM layers after max pooling layer. Model uses relu as activation function. And dropout probability is set to 0.01. The complete system runs for 10 epoch and accuracy and loss are calculated to get the performance of proposed hybrid model.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 15, 64)	1664
max_pooling1d (MaxPooling1D)	(None, 14, 64)	0
conv1d_1 (Conv1D)	(None, 14, 32)	6176
max_pooling1d_1 (MaxPooling1	(None, 13, 32)	0
lstm (LSTM)	(None, 13, 128)	82432
lstm_1 (LSTM)	(None, 13, 128)	131584
flatten (Flatten)	(None, 1664)	0
dense (Dense)	(None, 64)	106560
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 16)	1040
dropout_1 (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 1)	17

Fig.6 CNN-LSTM model

IV. RESULT AND DISCUSSION

A. Dataset Description

Soil dataset to predict the crop for Maharashtra district (Pune / Raigad / Nagpur) is downloaded from https://soilhealth.dac.gov.in/PublicReports/NSVW_total. It contains pH, EC, OC, N, P, K, S, Zn, Fe, Cu, Mn,B, etc. features and has time period of 2020 - 2021.

B. Experimental Setup

All the experiments are performed on environment of Intel i5, 3.2 GHz, 8 GBs of RAM, 1 TB of hard disk, 512 GB of SSD and Windows 10 operating system. Anaconda (Jupiter Notebook) IDE is used and Python 3.7 technology is used.

C. Performance Parameters

The proposed hybrid deep learning models (CNN +LSTM) results are compared to Naive Bayes, Random Forests, and SVM. The agricultural dataset is classified using these classifiers and the recommended multiclass model in the test on 10 fold cross-validation. A range of performance metrics are used to evaluate the accuracy of selected classifiers. To validate the findings of the proposed hybrid deep learning classifier and other classifiers, the classification accuracy, precision, and recall are determined. These metrics are calculated using the below formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

TP, TN, FP and FN are true positive, true negative, false positive and false negative values respectively. Accuracy, precision and recall scores of all the classifiers are represented in Figure 7 to Figure 10.

The classification methods were used to a multi-modal data set that included input data from IoT sensor data. The results of the performance evaluation of several categorization techniques are shown in Table 5. Naïvebayes had the lowest performance when compared to the others making it inappropriate for learning complicated structures for the subject data. All other classification models were surpassed by the proposed system (CNN + LSTM), which had the best accuracy, precision, recall, and F1 Score.

TABLE II. PERFORMANCE PARAMETERS COMPARISON OF ALGORITHMS

	Precision	Recall	F-Measure	Accuracy
NB	69	65	56	65
RF	85	85	84	85
SVM	91	91	90	91
CNN +LSTM	**95**	**96**	**95**	**95**

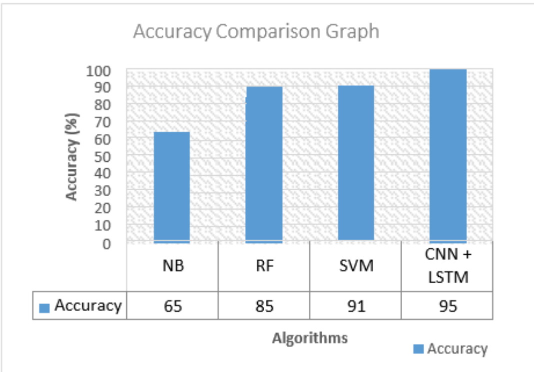

Fig 7. Accuracy comparison graph of ML and Hybrid DL algorithms

Figure 8 shows the training and validation accuracy comparison of CNN + LSTM model for 10 epochs. The validation accuracy after 10 epochs is 95.20 %. With increase in number of epoch the accuracy remains nearly same as shown in figure 8.

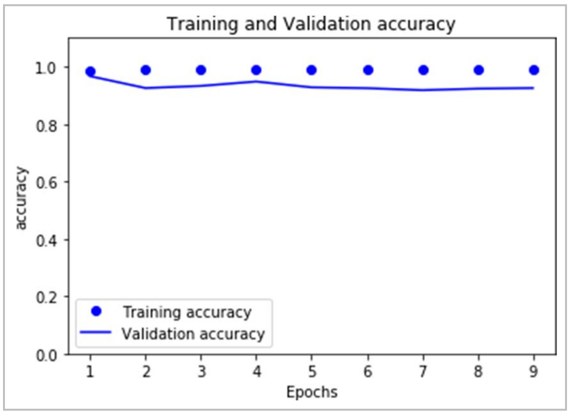

Fig 8. Training and validation accuracy comparisonof CNN + LSTM

Figure 9 shows the training and validation loss comparison of CNN + LSTM model for 10 epochs. The validation loss after 10 epochs is 0.08. With increase in number of epoch the loss is reduced whichcan be seen in figure 9.

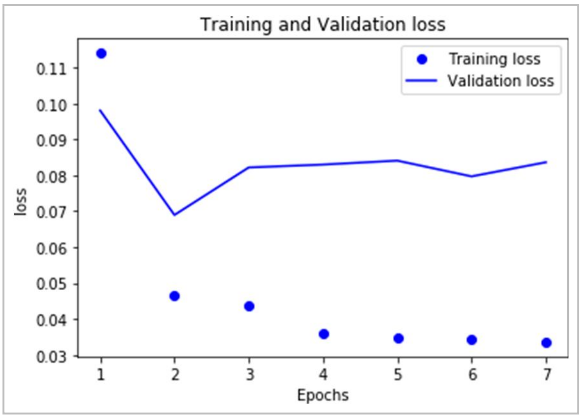

Fig 9. Training and validation loss comparison ofCNN + LSTM

V. CONCLUSION

Machine learning is a scientific field that has applications in crop prediction research. Farmers are keen to find out how much they can expect to produce, therefore crop cultivation forecasting is critical in agriculture. Previously crop yield prediction is used tobe done by taking into consideration farmers' fundamental knowledge of specific areas of land and the crops that will be cultivated there. Several machinelearning and deep learning technologies are utilised and analysed in agriculture to anticipate future crop production or which crop to be take in that soil. Our study focused on use of IOT sensors to collect real- time data from the farm, as well as employing feature selection methods to extract relevant features for prediction models. Propose system uses traditionalmachine learning algorithms and proposed hybrid classification model (CNN + LSTM) to forecast the crop perdition. Our findings reveal that Hybrid CNN +LSTM classifier beats other approaches with 10 fold and 80%–20% data splitting range and gives maximumaccuracy of 95.20 %.

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