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AI-DRIVEN PRECISE IRRIGATION FOR SUSTAINABLE FRUIT CULTIVATION USING IOT AND DEEP LEARNING

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Abstract— Precise irrigation is currently attracting a lot of attention as the global population continues to rise, increasing the demand for food and water. As a result, farmers will require water and arable land to meet this demand. Due to the scarcity of both resources, farmers need an alternative solution that modifies their operations. Precision irrigation is the solution for producing larger, higher-quality, and more efficient yields with limited resources. The application of Deep Learning (DL) and the Internet of Things (IoT) is essential for transforming irrigation into a more productive and ecological system. In this research, we used DL and IoT for smart irrigation to improve fruit productivity. For profitable yields, the first important step is to choose the appropriate fruit based on soil and environmental conditions. Next, the fruit should be grown in a controlled environment. For fruit prediction, the Stacked Long Short-Term Memory (Stacked-LSTM) model is used, and to maintain the controlled environment and detect abnormalities, the K-means clustering (KMC) algorithm is used. Both models are validated and deployed in the cloud. The Stacked LSTM model achieves an accuracy of 98.33%, and KMC yields a minimum relative error of 2.49%. Environmental parameters from the field are collected using sensors and sent to the cloud. The DL model in the cloud analyzes the data and provides required results, such as suggesting the appropriate fruit for cultivation. If any environmental factor increases or decreases beyond the normal range, it gives a notification. To provide all these facilities in a user-friendly way, an interactive website is developed.

Keywords—*Smart Irrigation, Internet of Things, Fruits, Stacked Long Short Term Memory, Firebase, Sensor, Deep Learning.*

Introduction

Machine Learning (ML) and Artificial Intelligence (AI) open up new possibilities in a wide range of industries, from smart agriculture to healthcare and finance, all because of huge data collected by sensor networks [1]. According to the US Department of Agriculture, the agriculture sector employed 10.9% of the workforce and contributed $1.109 trillion United States Dollar (USD) to Gross Domestic Product (GDP) [2]. This paper proposes a comprehensive strategy for automating soil conditioning systems that include a real-time sensor network linked to the cloud, algorithm-powered controllers, and advanced DL algorithms. The article focuses on the long-term viability of fruit farming. Smart farming systems can use real-time monitoring equipment and sensory data to improve crop quality and quantity, reduce costs, and promote sustainability by collecting high-resolution data from the field and surrounding environment. The economy and the establishment of a sustainable supply across a wide range of crops have prompted academics to focus on yield prediction techniques [3]. For the majority of the country's economy, fruit is an important crop. The global importance of fruit crops has prompted researchers to investigate how environmental conditions and soil physical qualities affect fruit quality rather than quantity.

To improve fruit production, farmers need to select the appropriate fruit based on the environmental and soil conditions. After cultivating, maintaining control over these conditions is crucial for achieving profitable yields. Excessive or insufficient levels of various physical parameters can negatively impact the quality and quantity of the fruit. To address this, we utilized advanced technologies in Deep Learning (DL) and IoT. In this research, DL and IoT are employed to identify the appropriate fruit for cultivation and monitor whether environmental factors are within the acceptable range. Before starting the research, several works on agriculture using advanced technologies were studied and are described below.

The article [4] describes a LoRa-based ML system for monitoring and scheduling correct irrigation using the IoT. Using data from soil moisture sensors, an automated irrigation system was designed that provided just what the eggplants and tomatoes needed. Water usage was reduced by 46% with the proposed technique compared to conventional watering, and the plants looked healthier as a result. According to the simulation results, the proposed system uses water far more efficiently in the experimental farming area than current methods. The study [5] presented the smart agriculture control system that collects environmental data and integrates it with an autonomous watering system. By merging data from IoT devices with an automated irrigation system, the proposed method assists farmers in expanding cultivation and ensuring crops receive an adequate water supply. During the growing season, vital field data such as humidity, temperature, light intensity, soil moisture, and ultraviolet range are recorded with IoT devices. Users can utilize the acquired data to continuously monitor the field at the given user address. Once the data has been received for processing, a fuzzy logic controller (FLC) is chosen to build a smart watering system. The effectiveness of the proposed technique was demonstrated by testing and evaluating the performance of the smart agricultural module in various environmental circumstances. The research [6] aims to create an ML model capable of estimating soil moisture levels. The model was trained and tested using data from the University of California, Irvine's publicly available Smart Irrigation System Dataset. The classification accuracy of the ResNet50 model was assessed using various performance metrics. The suggested model correctly classifies positive and negative samples 95% of the time. Furthermore, compared to other well-known ML models, the model outperforms most traditional methods. These findings have significant implications for the development of smart irrigation systems in precision farming.

The research [7] describes a novel technique for upgrading farming systems that incorporates Artificial Neural Networks (ANN) into irrigation management. The primary objectives are to improve crop health and resource efficiency through an automated decision-support system based on ANN insights, gather and track real-time data, and perform accurate data analysis for precise irrigation control. Using the provided training data, three models were trained: the proposed ANN model, the LSTM model, and the Convolutional Neural Network (CNN). The proposed model is evaluated and compared to CNN and LSTM algorithms to establish its effectiveness. When all criteria were considered, the ANN model stood out for its exceptional ability to accurately categorize moisture and temperature data, crucial for precision irrigation control. The study [8] suggests a sensor-based intelligent control system that uses IoT to implement smart agriculture approaches such as environmental data gathering and autonomous integration of irrigation systems. By merging data from IoT devices with an automated irrigation system, the proposed method assists farmers in expanding cultivation and ensuring crops receive an adequate water supply. Throughout the growing season, critical field data is collected using IoT devices. Users can utilize the acquired data to continuously monitor the field at the given user address. Once the data has been received for processing, an FLC is employed to build a smart watering system. The effectiveness of the proposed approach was validated by testing and evaluating the smart agricultural module's performance under various environmental conditions.

The paper [9] presents a hybrid ML-IoT model for yield prediction. This approach consists of three stages: preprocessing, feature selection, and classification. The first steps are dataset preprocessing and feature selection using the correlation and variance inflation factors. A suggested smart agriculture system based on the IoT uses a two-tier ML model. The Adaptive k-Nearest Centroid Neighbor Classifier model in the first layer proposes soil quality estimation and sample classification based on input soil parameters. The Extreme Learning Machine (ELM) approach is used to predict crop yield in the second tier. The upgraded technique uses a modified version of the Butterfly Optimization Algorithm to update the weights, lowering error levels and improving ELM performance accuracy. The article [10] discusses using the IoT to implement smart farming. The suggested system's primary goals are automatic water irrigation and plant disease detection. Based on agricultural requirements, it applies ML algorithms to accurately forecast when crops will require water and to automatically identify pests. To reliably forecast plant ailments, the pest detection module uses a K-Nearest Neighbor and support vector machine. Beneficial properties were derived from plant leaves. Classification is then conducted utilizing the gathered features. To assess whether a plant has a pest infestation, relevant features must be extracted and categorized. The suggested system monitors, analyses, evaluates and regulates operations to automatically irrigate agricultural areas and diagnose plant illnesses. The paper investigates the numerical analysis of ML algorithms as well as the significance of precise categorization.

Methodology

The methodology used to enhance the smart irrigation system for fruit production is detailed in this section.

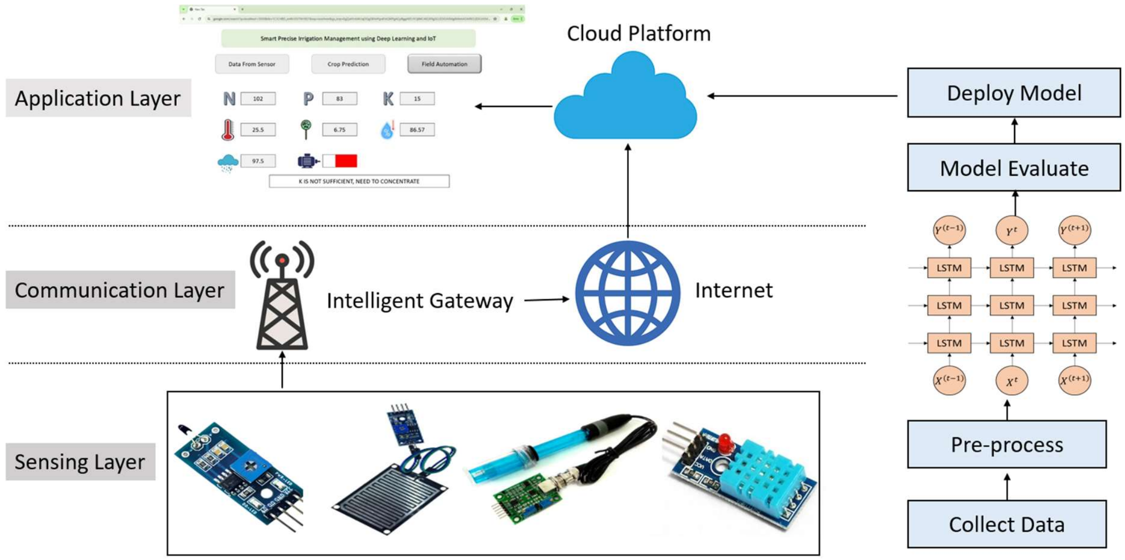

Fig. 1. Proposed DL and IoT methodology frameworkThe methodology starts with designing two DL models: Stacked LSTM for fruit prediction and KMC for detecting abnormalities in environmental factors. Both models are constructed, trained, and validated. After achieving satisfactory results, both models are deployed in the cloud to implement smart irrigation in real-time. Sensors are installed in the field to collect soil and environmental parameters. The sensor values are sent to Firebase using a Raspberry Pi, which helps in communicating the real-time data to the cloud. The developed DL models, already deployed in the cloud, use this real-time data to guide users in selecting the appropriate fruit for cultivation and understanding the environmental conditions. If any parameter deviates from the required range, a notification is sent to the user. To make the proposed methodology more user-friendly and interactive, a website is built. The proposed methodology framework is illustrated in Figure 1.

Deep Learning

Data acquisition and processing: The data used for smart irrigation of fruit production is taken from the Kaggle site [11]. The dataset consists of seven input features and a target. These input features include the soil's nitrogen ratio (N), the phosphorus ratio (P), the potassium-to-soil ratio (K), temperature in ^{0}C, humidity as a %, soil pH value, and rainfall measured in millimeters (mm). The dataset includes 22 crops, from which only fruit samples are selected. Each instance from the fruit data is given in Table 1. For each fruit, there are 100 samples, totaling 900 data samples. The last column in the dataset is categorical, representing fruit names. Label encoding is employed to convert the fruit names into numbers, decoding them to values between 0 and 9. The collected data has no missing values. Features like N, P, K, and Rainfall, which have values greater than 100, are scaled to the range of 0-100.

Table 1.Sample data

N	P	K	Temperature	Humidity	pH	Rainfall	Label
2	24	38	24.55982	91.63536	5.922936	111.9685	pomegranate
111	87	48	26.39855	81.36029	5.571401	98.16752	banana
1	35	34	30.79376	46.69537	6.273398	92.21319	mango
38	135	203	41.36106	82.79783	6.444373	69.92107	grapes
100	18	52	26.20234	80.38266	6.876067	56.47942	watermelon
91	13	47	29.10968	92.43511	6.144109	27.95602	muskmelon
28	123	202	22.76643	92.12439	6.442289	120.436	apple

30	7	15	33.23453	91.06054	7.825532	115.766	orange
69	60	54	36.32268	93.06134	6.989927	141.1737	papaya

After the pre-processing steps are completed, the data is split into two categories: 80% for training and the remaining 20% for testing. The training data holds 720 samples, and the testing data holds 180 samples. The distribution of fruit data for precise agriculture is shown in Figure 2.

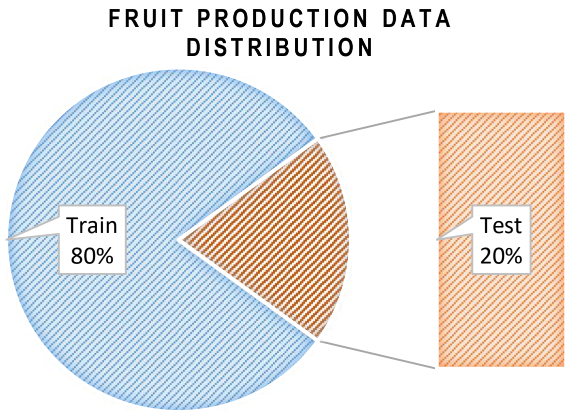

Fig. 2. Train and test data distribution

Once the preprocessing and data splitting are completed, 80% of the data is given to the DL model for training and validation purposes. The DL model is employed for crop prediction.

Stacked LSTM: Based on the research, a Stacked LSTM model was proposed for implementing smart irrigation. The architecture of stacked LSTM is given in Figure 3. To predict the crop based on irrigation data, an LSTM, a subset of the RNN model, was used. Each LSTM unit comprises four gates: input gate, forget gate, output gate, and cell [12]. The initial parameters for an LSTM unit are $c_0 = 0$ and $h_0 = 0$, and the equations for the unit are given below:

$$f_t = \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right) \quad [1]$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \quad [2]$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad [3]$$

$$\tilde{c}_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \quad [4]$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad [5]$$

$$h_t = o_t \odot \sigma_h(c_t) \quad [6]$$

The subscript t indexes the timestep. $x_t \in R^d$ represents the LSTM's input vector, and $f_t \in (0,1)^h$, $i_t \in (0,1)^h$, and $o_t \in (0,1)^h$represents the activation vector of forget gate, input gate and output gate, $h_t \in (-1,1)^h$ represents the LSTM unit's hidden state or output vector. $\tilde{c}_t \in (-1,1)^h$ represents the cell input's activation vector, $c_t \in R^h$ is the cell state vector. $b \in R^h$, and $W \in R^{h.d}$ represents the bias and weight parameters updated in the training stage, where h and d represents the number of hidden units and input features.

Overfitting the training data, which causes the model to learn statistical noise, is a significant issue in training a complex model [13]. Poor performance may arise when the model is applied in various scenarios. To mitigate these issues, the dropout approach is employed.

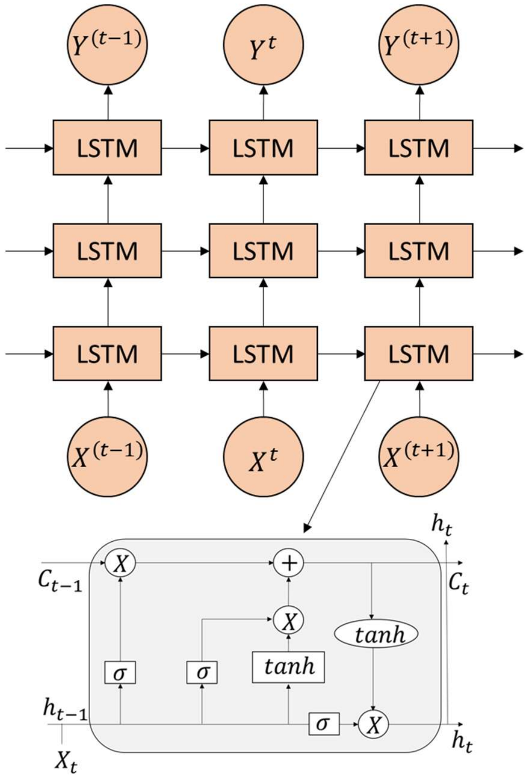

Fig. 3. Stacked LSTM architecture

Dropout is used to randomly remove nodes from the model's hidden and input layers. This technique helps the network focus on learning essential features by reducing reliance on specific nodes, thus enhancing generalization capability. Dropout modifies the forward propagation equation as follows:

$$r_j^{(l)} \sim Bernoulli(p) \qquad [7]$$

$$\widetilde{y^{(l)}} = r^{(l)}.\, y^{(l)} \qquad [8]$$

$$z_i^{(l+1)} = w_i^{(l+1)} \widetilde{y^{(l)}} + b_i^{(l+1)} \qquad [9]$$

$$y_i^{(l+1)} = f\left(z_i^{(l+1)}\right) \qquad [10]$$

Here, z, y, w, and b represents the pre-activation, post-activation, weight, and bias of output vector from layer $(l + 1)$. A dropout layer is introduced after each LSTM layer in our model with a dropout rate of 0.1, removing 10% of the input nodes for each LSTM layer.

The loss function measures how far the actual targets deviate from the model's predicted outcomes. Minimizing this difference, aiming for the function's output to approach zero, signifies optimal model performance. The cross-entropy function is used, because the problem involves binary classification. However, various other loss functions are applicable depending on the model and task. The formula for binary cross-entropy loss is given in Equation (11):

$$-\sum_{n=i}^{c} t_i log\big(f(s_i)\big) + (1 - t_i) log\big(1 - f(s_i)\big) \qquad [11]$$

The inputs and their weights are denoted by s_i, the activation function by f, and the target estimation by t_i. Through optimization strategies, the model's learning process can be enhanced and subsequently updated. The loss indicates how closely the model approximates the target output. By determining optimal weights, these strategies help minimize errors in translating inputs to outputs. Adam enables dynamic learning rates. Adam's updating equations are as follows:

$v_t = \beta_1 . v_{t-1} - (1 - \beta_1) . g_t$ [12]

$s_t = \beta_2 . v_{t-1} - (1 - \beta_2) . g_t^2$ [13]

$\Delta w_t = -\eta \frac{v_t}{\sqrt{s_t + \epsilon}} . g_t$ [14]

$w_{t+1} = w_t + \Delta w_t$ [15]

The hyperparameters are represented by β_1 and β_2, initial learning rate by η, gradient at t is represented by g_t, gradient's exponential average is represented by v_t, and the square of each parameter s_t. An activation layer, appropriately selected and tailored to the current task, is necessary to define the final step in the prediction process: the weighted sum of the preceding layers. For addressing a binary categorization issue, thus the sigmoid function will be employed and it is defined in Equation (16):

$\sigma(x) = \frac{1}{1+e^{-x}}$ [16]

Where x represents the sigmoid function's input and e represents the Euler's number.

K-Means Clustering: The KMC is a widely used technique for grouping a dataset into K distinct, non-overlapping clusters [14]. Mathematically, the KMC approach is defined as follows: K denotes the total clusters, n represents the total data points, d represents the actual dimensions, x_i stands for data point i ($i \in 1$ to n), and c_k represents the centroid of cluster k. KMC seeks to decrease within-cluster variance, commonly referred to as distortion or inertia. This is determined by summing the squared distances between all data points and their cluster centroids. The explanation of algorithm is detailed below

1. Initialization: Begin by placing K randomly selected centroids c_k into each cluster.
2. Assignment: Each data x_i is assigned to the closest centroid using the Euclidean distance: $argmin_k \|x_i - c_k\|^2$ [17]
3. Updation: The centroids c_k are updated by calculating mean of all data points assigned to cluster:
   $c_k = \frac{1}{|S_k|} \sum_{x_i \in S_k} x_i$ [18]
   where S_k represents the set of x_i assigned to k.
4. Repeat the process 2 and 3 till it converged.

The objective of the clustering is to reduce the within-cluster sum of squares (WCSS):

$WCSS = \sum_{k=1}^{K} \sum_{x_i \in S_k} \|x_i - c_k\|^2$ [19]

Upon reaching a maximum number of iterations or if the centroids stabilize during iterations, the K-means algorithm converges. As soon as the data points converge, they are placed into one of the K clusters according to how close they are to the centroidc_k. With the goal of reducing inertia, variance, or the sum of squared distances during the iterative process, KMC produces a set of K clusters, each defined by its centroid. KMC converges when the centroids stabilize between iterations or when the maximum number of iterations is reached. KMC helps identify anomalies in the irrigation dataset. If any parameters deviate from the required levels, whether increasing or decreasing, they can be easily identified using this algorithm.

Wireless Sensor Network

Firebase is rapidly gaining popularity among software developers due to its capacity to work with "not only structured query language" ("NoSQL") data structures. These structures can manage a diverse set of data types, quantities, origins, and formats. Firebase provides data that is updated in real-time and responds quickly. Authentication, cloud messaging, database management, and API connectivity are some of the most popular Firebase uses among developers. For data processing, researchers typically utilize Firebase to send information from IoT devices to user systems [15]. One example is the monitoring of natural production parameters. Firebase now offers six core services: cloud messaging and alerts, authentication, analytics, real-time database, hosting, and cloud. To facilitate communication between end users and IoT devices, this study makes use of the Firebase real-time database service.

The IoT system has two endpoints. The first endpoint is the IoT device, which communicates with the Firebase Realtime Database and delivers data such as N, P, K, temperature, pH, humidity, absolute rainfall, and motor status, among other parameters. This endpoint then connects to the web application, which serves as the second endpoint. The web application reads the data, displays it on a visually appealing dashboard, and notifies the user of any irregularities in the physical parameters discovered.

Results and Discussion

For precise irrigation, we used two advanced technologies: DL and IoT. First, a Stacked LSTM is constructed and trained to accurately predict the suitable fruit for cultivation based on environmental factors. Next, the KMC algorithm is used to detect anomalies in environmental factors, indicating deviations from the optimal range. This helps in identifying environmental anomalies such as excessive or insufficient conditions, providing timely notifications. Secondly, the developed Stacked LSTM and KMC models are deployed in the cloud. Sensors and Raspberry Pi devices are utilized to collect real-time data from the field. The models deployed in the cloud handle fruit prediction and anomaly detection based on the collected data. A website is created for user interface purposes. The detailed outcomes of DL and IoT integration are outlined below.

DL Model Evaluation

The outcome of the Stacked LSTM model in training for the fruit prediction task is evaluated using accuracy and loss values. Figures 4 and 5 depict the accuracy and loss plots of the Stacked LSTM model during both the training and validation phases. In both phases, the accuracy value exceeds 0.99 and the loss is less than 0.1. The Stacked LSTM model is further evaluated using test data, yielding accuracy, precision, recall, and F1 scores of 98.33%, 97.78%, 98.88%, and 98.32%, respectively. These results demonstrate the excellence of the proposed DL model in fruit prediction based on soil and environmental conditions.

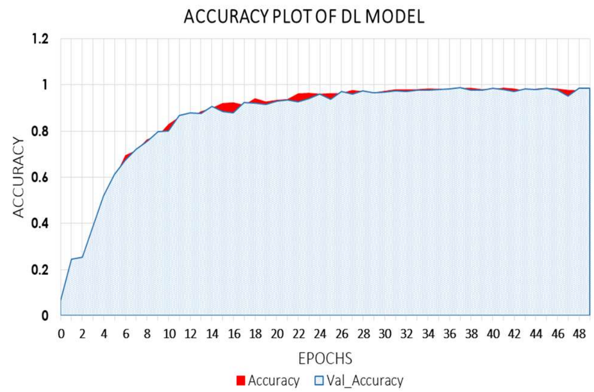

Fig. 4. Accuracy graph of proposed DL model

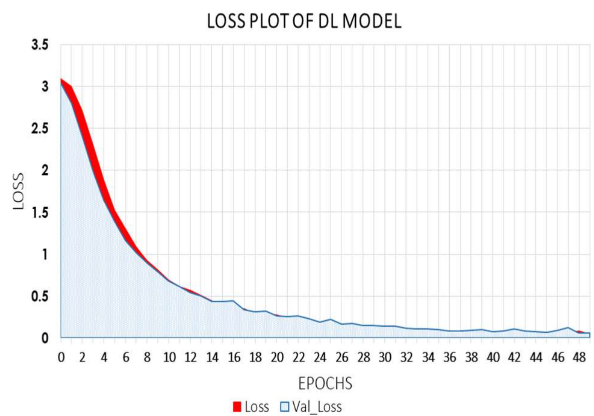

Fig. 5. Loss graph of proposed DL model

Table 2. Outcome of the DL model on

Metrics	Metrics Value (%)
Accuracy	98.33
Precision	97.78
Recall	98.88
F1-score	98.32

Next, the KMC algorithm is evaluated to detect anomalies in soil and environmental conditions. The KMC algorithm shows a relative error of 2.49%, indicating minimal discrepancy.

IoT Integration

After evaluating the outcomes of both models, we deployed them in the cloud. Real-time data including the physical parameters related to irrigation is collected from sensors and sent to Firebase. Figure 6 illustrates the acquisition of real-time data in Firebase.

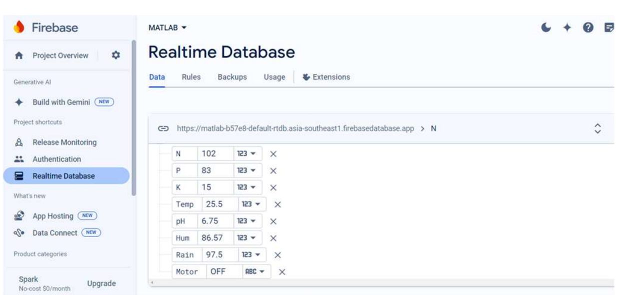

Fig. 6. Data collection in Firebase

The interactive website is designed and the functionality of the website is tested on the local host. The website displays sensor values from the field and enables users to predict the most profitable fruit for cultivation based on soil and environmental conditions using the Stacked LSTM model. Next, it identifies any abnormalities in soil and environmental variables using the KMC algorithm. Timely notifications of anomalies help users adjust their setup; for instance, if levels of N, P, or K are low, users can apply fertilizer. This highly automated and intelligent system helps mitigate losses in agriculture. The website's functionality is illustrated in Figure 7.

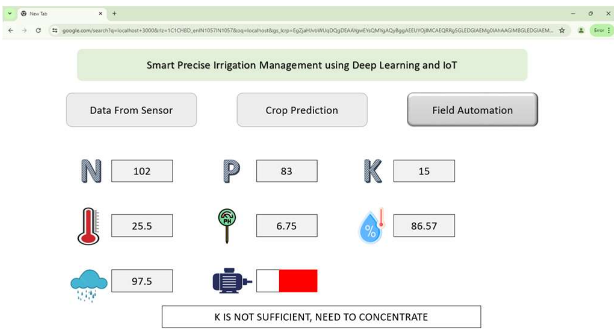

Fig. 7. Automated website for smart irrigation using DL and IoT

Conclusion

The research successfully developed a smart irrigation system to enhance fruit productivity using DL and IoT technologies. The environmental and soil data from 9 types of fruits were collected and processed. To predict the appropriate fruit based on environmental and soil conditions, the Stacked LSTM model was implemented, achieving excellent performance metrics: accuracy: 98.33%, precision: 97.78%, recall: 98.88% and f1-score: 98.32%. Next, to maintain a controlled environment, the KMC algorithm was implemented. It helps detect if any irrigation variables exceed or fall below the normal range. KMC detects abnormalities with an error rate of 2.49%. The DL model is deployed in the cloud. Finally, a user-friendly website was designed. The website allows users to view environmental and soil parameters and suggests the appropriate fruit to cultivate. It also sends notifications if any parameter is not within the proper range. This invention can help farmers enhance fruit productivity while using minimal resources.

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