ISSN: 2093-5374 / E-ISSN: 2093-5382

Predictive Crop Yield Analysis Using Deep Learning and Optimized Sensor Data in Precision Agriculture

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Received: May 21, 2025; Revised: July 03, 2025; Accepted: August 22, 2025; Published: September 30, 2025

Abstract

Precision agriculture is recognized as one of the essential practices for maximizing crop yield and optimizing resource utilization in agricultural practices. Deep learning algorithms, combined with high-quality sensor data, can extract useful information to make accurate predictions for crop yield on time. Because deep learning methods are adept at identifying patterns in large datasets, it's beneficial to apply them to projects such as predicting crop yield. Deep-learning models identify the intricate relationships between these variables and crop yield by leveraging data from sources such as weather reports, soil information, and crop health data. Finally, the deep learning model integrates with a portion of the optimized sensor data to enhance the precision of crop yield prediction. The sensors collect precise, in situ measurements of soil moisture and nutrients.

Keywords: Precision Agriculture, Resource Efficiency, Deep Learning, Leveraging, Accuracy, Sensors.

1 Introduction

It includes the use of computation then statistics toward assess the possible income in agriculture of a region. In the present approach, information is gathered and analyzed from weather, soil, and crop

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 3 (September), pp. 155-177. DOI: *10.58346/JOWUA.2025.I3.010*

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management data (Bakthavatchalam et al., 2022). The objective of a predictive crop yield forecasting system is toward offer appropriate besides correct forecasted material happening yield in the region to farmers, agribusinesses, farm management companies (FMCs), and policymakers during the fall season (Smihunova et al., 2024). They can receive small calls on the type of crops, seeding times, and amounts of inputs to produce crops more profitably (Gopi & Karthikeyan, 2024). Coursework to predict crop yield encompasses a range of methods and techniques, with remote sensing, machine learning, and statistical modeling (Salami et al., 2025). These have been previously applied to predict future crop yields using historical data, weather patterns, and other relevant variables (Mythili & Rangaraj, 2021). Remote sensing is all about collecting data on the health and development of crops using satellite imagery and various types of remote sensing technology to forecast yields. In the case of crop yield, big data can also assist machine learning algorithms in determining designs and forecasting yield. In contrast, statistical modeling involves writing formulas to predict past performance and future crop yields, as well as related field parameters (Fei et al., 2023). These models can be integrated with climate, soil health, crop management practices, or market conditions (e.g., price and demand) to enhance their predictive capabilities. An analysis of crop yield is a must on the farm. It contributes to understanding the crop production and predicting the future yields (Burdett & Wellen, 2022). In some cases, predictive crop yield analyses are often carried out using statistical, mathematical, and machine learning models for the basis of future crop yield estimation (Sarkar et al., 2024). It utilizes everything (history's output, the history of weather, soil productivity, market demand to make predictions. Even if this approach may be beneficial for farmers, several limitations exist in the usage of drones for distant detecting in plantations (Mythili & Rangaraj, 2021). The accuracy of predictive crop yield analysis depends on the availability and accuracy of the data (Veerasamy & Fredrik, 2023). This applies to items such as past crops, climate, and soil. Its forecasts can thus be unreliable in the presence of sufficient or the right data (Bharadiya et al., 2023). Due to the erratic weather patterns associated with climate change, most plants and food crops did not grow well. Much predictive crop yield analysis is based on historical weather data (Balavandi, 2017).

However, the times are changing, and the past may not be a reliable indicator of the future. Agriculture is a dynamic sector in which new crops, farming systems, and robotic technology are constantly being developed. These differences can include changes in crop yields and can be excluded from predictive crop yield models (Goel et al., 2022). The examined harvest yield analysis factors, for example, weather or soil type, but not external factors such as a given economic policy, trade insurance, or market demand. These alternative variables have the potential to affect CRA output in a large magnitude. Therefore, the model predicts that a few crop yields are disturbed. The primary contribution of the proposal is as follows,

- Predictive Crop Yield Analysis combines the strength of historical data with advanced algorithms and data analytics to provide accurate analyses of crop yields.
- Learning facts on numerous features of crop yield, such as weather conditions, soil health, and pest infections, Predictive Crop Yield Analysis can identify and warn of potential risks and suggest workable fixes for farmers. That might mean adjusting planting times, the type of fertilizers and/or pesticides used, or irrigation tactics.
- Producers can utilize Predictive Crop Yield Analysis to understand crop variety, resource usage, and pricing. It may offer them a route to increased profitability and resource sustainability on their farm.

The remainder of the research is prepared as surveys. Chapter 2 documents the relevant works done in the literature—the suggested model, as presented in Chapter 4, for comparative analysis. The resulting answer is provided at the end of Chapter 5, and conclusions and outlook are finalized in Chapter 6.

2 Related Words

Kumar et al., (2023) We have presented the Multiparameter Optimization System with DCNN (Deep Convolutional Neural Network), which is useful in exactness agriculture aimed at progressive irrigation planning and scheduling. Using soil moisture estimation can refine irrigation strategies for better water use efficiency. The DCNN machine learning technology enables precise and instantaneous analysis of multiple parameters for decision support in irrigation. Sakthipriya & Naresh, (2024) has presented Precision Agriculture, a farming technology that utilizes convolutional neural networks and machine-learning genetic algorithms to optimize nutrient application during rice cultivation. This technology processes images of rice fields to assess their nutrient status, enabling a fertilizer prescription to improve yield and input-use efficiency. Kashyap et al., (2021) have noted that precision agriculture enables farmers to apply new technologies, thereby increasing the amount of food they can produce while using the same amount of resources. Sikarwar et al., (2025) Such products may include IoT-integrated smart irrigation systems that utilize deep learning networks to analyze real-time data and adjust irrigation settings accordingly. This enables farmers to make better decisions, using less water while growing more crops. Sivakumar et al., (2022) It has been explained that the Internet of Things is a system of connected devices (such as physical devices and vehicles embedded with software, sensors, and network connectivity) that collect and exchange data. Clustering of Sensors & Devices Smart Sensors / Devices 1 2 3 4 Sensors and Appliances Let's assume an IoT. Intelligent precision agriculture utilizes applications that rely on IoT and machine learning to screen and analyze data from weather, soil quality, and crop health information, thereby informing better growing practices and enhancing agricultural output. (Patil et al., 2024) investigated the Precision Agriculture Model for Farm Irrigation, which employs machine learning algorithms to process data, such as soil moisture and weather, to enhance water usage for crops. This model assists farmers in deciding when and how much to apply water, thus ensuring optimal irrigation and enhancing crop yield. Ju et al., (2021) introduced this study, which utilizes variables based on MODIS and meteorological data to predict crop yield at the county level. Alibekova et al., (2025) have benchmarks various machine learning models in this task. This strategy container service growers and decision-makers make informed decisions about crop management and resource allocation. Shaikh et al., (2022) discussed that precision agriculture and smart farming can use machine learning and Artificial intelligence to process huge databases and offer useful insights for better decision-making. Such technologies can help enhance crop management efforts, productivity, and efficiency while also reducing costs and environmental impact. Saranya et al., (2023) have previously presented Deep learning and the Internet of Things (IoT) as two fast-growing technologies that offer much to precision agriculture. Deep learning involves teaching artificial neural networks to interpret large quantities of statistics, whereas IoT focuses on connecting sensors and devices to enable continuous monitoring and real-time adjustments. Comparing those technologies can provide a picture of their potential applications and benefits for precision agriculture. Kganyago et al., (2024) have explained the use of remote sensing images in optical sensing, which utilizes sensors to obtain information on a crop's biophysical and biochemical parameters from the ground level. Recent expansions trendy device equipment and machine learning algorithms have enhanced the accuracy and precision of this approach, creating a valuable application for precision agriculture. Dakir et al., (2021) have provided a review of some successful applications of Artificial Intelligence (AI) in precision agriculture. These applications include: (1) satellite remote sensing to track plant health and soil moisture level records in real-time,

(2) the use of AI algorithms on this information for making knowledgeable choices on crop management and resource allocation, and (3) the implementation of AI systems for executing automated precision farming methods. It can lead to more efficient and economical farming practices, increased crop yields, and sustainable agricultural practices. Chaudhary et al., (2024) have outlined crop management, a critical aspect of agriculture that significantly impacts crop quality and quantity. As ML methods continue to mature, tracking records of weather, soil, and plant life whenever a decision is made can become possible. This could lead to intelligent, sustainable management of the farms, resulting in maximum productivity with reduced costs and a lower environmental impact. Senapaty et al., (2023), A system based on the Internet of Things (IoT) for soil nutrient analysis and crop recommendations in precision agriculture. It collects real-time nutrient content in the soil and crop growth parameters using sensors and analyzes the data. It provides tailored fertilizer and crop recommendations to optimize yield and sustainability. It enables farmers to make informed decisions using data and farm most efficiently compared to traditional farming methods. Mancipe-Castro & Gutiérrez-Carvajal, (2022) propose predicting environmental variables in precision agriculture using a sparse model that fuses information from different sources to achieve higher accuracy. This model utilizes soil, weather, and plant data to predict and inform decision-making regarding best practices for crop growth, yield, and resource use. Nasir et al., (2021) proposed a Profound knowledge-based classification of fruit diseases as a technique to precisely detect and classify crop diseases by employing modern machine learning techniques. This technique utilizes a vast amount of images of normal and diseased fruits to train a model that can be applied for the early detection and control of diseases in precision agriculture. Mehedi et al., (2024) We have reviewed Remote sensing, which is the acquisition of data on an object or phenomenon that occurs at a distance from the object and is a domain that is increasingly used in precision agriculture. The integration of FM with decision support systems can provide farmers with critical information and knowledge about their crops, supporting decision-making and optimizing agricultural management practices. Nevertheless, there are still some issues that limit the application of these methods, e.g., data accuracy and availability Table 1.

Table 1: Comprehensive Analysis

Authors	**Year**	**Advantage**	**Limitation**
Kumar et al., 2023	2023	Real-time and accurate estimation of soil moisture levels allows for more efficient water usage and improved crop yield.	The system may not be able to accurately account for variations in soil composition and crop types.
Sakthipriya & Naresh, 2024	2024	Improved accuracy and efficiency of fertilizer application based on precise crop nutrient needs, leading to higher yields and reduced input costs.	Difficulty in obtaining accurate and real-time data due to hardware and sensor limitations in agricultural fields.
Kashyap et al., 2021	2021	Improved crop yield and water efficiency through real-time data collection and analysis for personalized irrigation schedules.	Limited access and connectivity in rural areas could restrict the implementation and effectiveness of theIoT-based intelligent irrigation system.
Sivakumar et al., 2022	2022	Improved crop yield and resource management through real-time data monitoring and predictive analytics.	Limited access to reliable and affordable high-speed internet connection in rural areas may hinder effective data collection and analysis for smart precision agriculture.
Patil et al., 2024	2024	Maximizes crop yield while conserving water resources, resulting in increased profits for the farmer and sustainable farming practices.	Requires constant updating and calibration for changing environmental and soil conditions, which can be time-consuming and labor intensive.

Ju et al., 2021	2021	Improved accuracy in predicting crop yield can aid in maximizing agricultural production and reducing economic losses for farmers.	The reliability of the prediction may be limited by the quality and availability of the data used for training and testing the models.
Shaikh et al., 2022	2022	Improve efficiency in decision making by providing timely and accurate data analysis for better crop management and resource optimization.	Limited access to advanced technology and resources by small-scale farmers.
Saranya et al., 2023	2023	By combining deep learning and IoT, precision agriculture can optimize farming practices and improve crop yields through data-driven decision making.	Limited data availability or inconsistent data quality may affect the accuracy and reliability of both deep learning and IoT in precision agriculture applications.
Kganyago et al., 2024	2024	Optical remote sensing allows for non-destructive and large-scale monitoring, providing valuable information for precision agriculture and crop management.	Limited accuracy and reliability in estimating crop parameters due to the presence of clouds and atmospheric conditions affecting image quality.
Dakir et al., 2021	2022	Better crop yield predictions can be made with AI's ability to analyze large amounts of satellite data, improving farming decision-making and resource allocation.	One limitation could be the high cost of acquiring and maintaining satellite imagery and data, making it inaccessible for some farmers.
Chaudhary et al., 2024	2024	Improved decision making through data-driven insights and predictions leading to increased efficiency and yield potential in crop management practices.	Reliance on accurate and up-to-date data may be hindered by lack of access or poor data collection methods.
Senapaty et al., 2023	2023	Precision agriculture can lead to increased crop yields and reduced use of fertilizers, resulting in improved sustainability and cost-effectiveness for farmers.	The model may not take into account other variables that can affect crop growth, such as weather, pests, and soil moisture.
Mancipe-Castro & Gutiérrez-Carvajal, 2022	2022	Efficient resource management and increased crop yields through accurate prediction and analysis of environmental factors such as weather, soil conditions, and crop health.	Difficulty in accurately capturing contextual information and potential bias from incomplete or biased data sources.
Nasir et al., 2021	2021	One advantage is that it can accurately identify plant diseases in real-time, allowing for promptand targeted treatment to prevent crop loss.	Possible overfitting of the model due to limited diversity in training data, leading to reduced accuracy when tested on new data.
Mehedi et al., 2024	2024	One advantage is improved crop yield and resource management through advanced data analysis and real-time monitoring of field conditions.	The accuracy of remote sensing data can be affected by weather conditions, cloud cover, and sensor limitations, leading to potential errors in decision making.

- Unreliable data collection: As with any obvious issue with predictive crop yield analysis, on top of the line, the data collected will be extremely misleading. Unequal parameter discrepancy in consolidated data from various sources creates a bottleneck, making precise prediction mostly unreliable.
- It relies on weather data to predict crop yield and forecasts but MANNI is not able to provide accurate weather forecasting. Crop yield prediction is a much more sensitive matter and any

inaccuracy due to weather forecasting might cause the crop yield prediction to be inaccurate as well. Plus, historical weather data might not be indicative of current climate change trends and may provide inaccurate forecasts.

- Most of the harvest produce prediction models are dependent on historical data and at times do not hold to the current status of crops. Real-time data integration is the answer and the likely single biggest advancement that will be made in producing a better yield analysis.

It has changed the way farming is done. Deep learning algorithms learn large amounts of data from sensors in contrast to using weather, soil, crop health detectors, etc., because it is used through advanced machine learning techniques. It provides live monitoring and diagnosis for crops that can be used to make precise and more efficient decisions. In addition, the optimization of sensor data via processes such as filtering and interpolation helps to mitigate noise and improve the quality of the gathered data. The amalgamation of deep learning and enhanced sensor data not only enhances the output and yield of the crops but also reduces the wastage of resources and helps in the conservation of agriculture practices.

3 Proposed Model

A. Construction Diagram

- **Database**

A database is just a system through which you can store, edit, add, or retrieve data. It is composed of several tables, and fields that belong to different categories of data. Data manipulation, such as adding, updating, and deleting information in the database, can be considered one of the most important operations of a database. Usually, it uses a query language such as SQL to facilitate it make complex searches, and fetch specific data. Key other functions are also performed such as indexing (makes data fetching quicker) and transaction management (data remodelling is consistent). It also includes security measures such as authentication to keep private data safe from unauthorized users and backup and restore mechanisms in case of data loss. For proper organization of Data and Information Databases is important for different organizations to handle their data more effectively.

- **Data Pre-processing**

Data pre-processing is a critical step in data mining that involves transforming raw data into a clean, understandable format for analysis. This stage, in general, entails data cleansing and manipulation to address errors or outliers that might compromise the accuracy of the findings. Cleaning includes removing irrelevant or duplicate data, handling missing values, and correcting inconsistencies or errors.

During an agent's lifespan, finding the best policy to maximize the overall discounted reward is its main goal. Equation (1) defines the ideal policy.

$$\pi*(q) = \arg\max_{j \in J} \gamma \sum_{q' \in Q} F_{qj}(q', j) T^*(q', j) \tag{1}$$

$$\pi*(q, j) = L(q, j) \max_{j \in J} \gamma \sum_{q' \in Q} F_{qj}(q', j) T^*(q', j) \tag{2}$$

$$Loss = \left(l + \gamma \max_{j'} S(q', j'; \theta') - S(q, j; \theta)\right)^2 \tag{3}$$

On the other hand, data transformation consists of converting the data into a format suitable for analysis, such as normalizing or scaling the data. This ensures that the data is consistent and ready for further processing and analysis, increasing the accuracy and reliability of the results. Data preprocessing is a vital stage in data mining as it sets the foundation for accurate and meaningful insights to be extracted from the data.

- **Train Data**

Train data is just a set of information that is sent to a computer model or algorithm to teach it stuff. Normally in such a way that the computer can learn patterns and predict based on that data. To train a model, you give it lots of data and adjust the model or algorithm, called a learning algorithm, to improve the performance of the model on that data. In training and testing, the data is split up to test how good your model is doing. When trained, the computer will practice regression, classification, and clustering techniques to understand the data and recognize the patterns. Figure1 Shows The construction diagram has shown in the following.

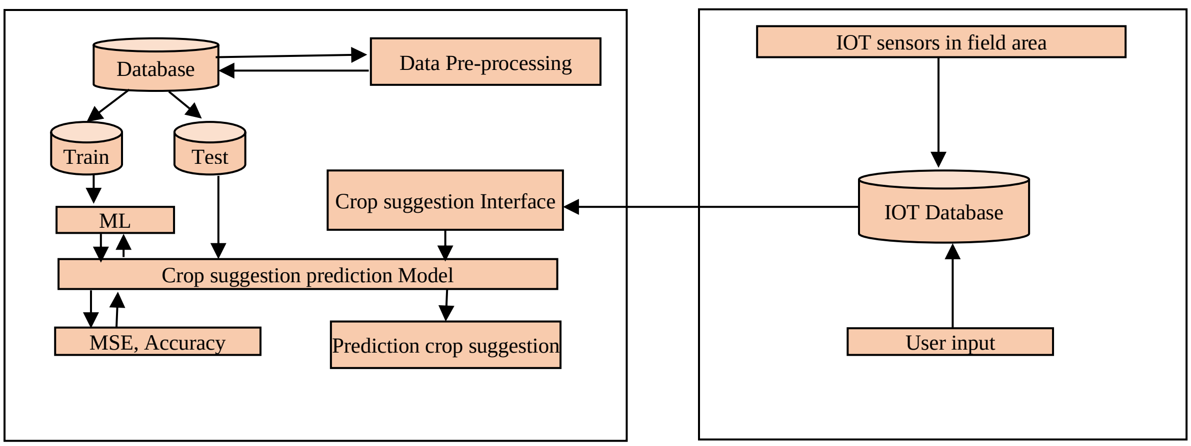

Figure 1: Construction Diagram

This allows the model to make accurate predictions on new data it has not been trained on before. Continuous training with new data is also essential to improve the accuracy and effectiveness of the model over time.

- **Test Data**

Importance of Test Data in Software Testing Test data is one of the most important things in software testing where it helps the software testing to verify the quality of the software and how reliable the software with its quality through demonstration of how accurately it can able to measure the software product. The unique data that is used to design and test the efficiency of a program or system is known as the test data. The test data is used to represent real-life scenarios and take all the possible combinations of the input test data, which results in a defect or an error if there are any flaws or errors in the SUT. This means that generating or modifying different data sets to invoke other responses should enable the ability to predict the behavior of software in multiple scenarios. It is even used in performance testing; to test the load, speed, and effectiveness of the software on different paying loads.

- **Machine Learning**

Machine learning is a subset of artificial intelligence that allows computer systems to learn and improve from experience without being explicitly programmed automatically. It involves creating algorithms that can analyze and interpret large amounts of data, identify patterns, and make predictions or decisions based on that data.

$$X^{t} = p\left(o \times h^{t} + z \times X^{t-1} + i_{1}\right) \tag{4}$$

$$U^{t} = p\left(t \times X^{t} + i_{2}\right) \tag{5}$$

$$R = U^{t} - k^{t} \tag{6}$$

$$W\left(h,k\right) = p\left(\sum_{b=0}^{B}\sum_{A=0}^{A} B\left(h+b,k+a\right) * M\left(b,a\right) + i\right) \tag{7}$$

A training phase where the machine is fed a rich dataset and it starts learning all these patterns/relationships.Which allows us to have a model that can predict and give decisions on new data. ML Flow tracks the entire machine learning model life cycle, including data pre-processing records, model building and training information, and end-to-end model evaluation for accuracy and effectiveness. The adaptation of machine learning algorithms due to continuous learning makes them very reliable in solving complex problems and predicting accuracy in various domains like finance, healthcare, and marketing.

- **Crop Suggestion Interface**

The crop suggested interface is a software application that helps farmers select the best crop that they want to grow, here you can suggest as per soil type, climate, demand, etc. This interface makes use of a database, which contains varied information about different crops, and an advanced algorithm that can predict the characteristics of the land of a farmer to bring in recommendations. Factors such as soil pH, nutrients, moisture levels, historical data, the current market trends (and more) are taken into consideration. This also opens the door for farmers to give a personalized touch to their preferences as well as goals to modify the recommendations. This then supports farmers to make better choices and earn better produce thereby increasing their profit. The UCERF front end is designed to adapt based on feedback (the service continually learns), making it a living system useful to planners in the agricultural sector.

- **Crop Suggestion Prediction Model**

The crop prediction model's recommendation is an intelligent tool that predicts suitable crops for a specific location. The model is trained on weather conditions, soil features, historical crop success, and other inputs to forecast conditions and recommend crops that are expected to thrive. The model takes into account more than a dozen factors, including temperature, precipitation, sunlight, and available nutrients, to forecast the likelihood of various crops succeeding. The input of any pests and diseases in the region is also considered. Using a host of more specific data points and working through this process, the model is then in a position to provide well-founded, trustworthy crop suggestions that farmers can take and then use to make decisions.

- **MSE, Accuracy**

Mean Square Error (MSE) is a popular metric used to evaluate the performance of regression models. It measures the average squared difference between predicted and actual values. MSE is calculated by taking the sum of the squared errors and dividing it by the total number of data points. This metric is helpful because it penalizes significant errors more than smaller ones, giving a more accurate measure of the model's accuracy.

Following the completion of convolution layers, the system is subjected to an activation function, which is a nonlinear function.

$$j_r = p\left(Z_{r-1}, rjr - 1 + I_r + Z_{r-2}, rjr - 2\right) \tag{8}$$

$$\Delta Z_{r-1}, r = -\eta \frac{\sigma G_r}{\sigma \omega_{r-1,r}} \tag{9}$$

$$\Delta Z_{r-2}, r = -\eta \frac{\sigma G_r}{\sigma \omega_{r-2,r}} \tag{10}$$

$$f\left(k_b \left| h_1, \ldots.., h_{b-1}, k_{b-1}\right.\right) \tag{11}$$

On the other hand, accuracy is a metric used to evaluate classification models. It measures the percentage of correct predictions from the total number of predictions made. In other words, it shows how well the model can correctly classify data into their respective categories. MSE and accuracy are essential metrics in evaluating model performance, and their values can help determine the effectiveness and reliability of the model.

- **Prediction Crop Suggestion**

It is recommended to perfect crops at a desired location by using data analytics and futuristic technologies. Usually, data is collected on distinctive factors that affect the area, such as the climate, soil dimension and health, and the historical crop yield in that region. The data is subsequently analyzed using algorithms and machine learning models to detect patterns and relationships among variables. The system can predict which crop would be most likely to yield success in that particular area based on this analysis. By considering market demands, rotation, and possible disease. Ultimately, the idea is that farmers receive accurate and actionable advice that is highly personalized and allows them to make better decisions, and get more from every acre.

- **IoT Sensors in Field Area**

These field-deployable devices are designed to measure and track subjects external to their inner workings These sensors have different types such as temperature, humidity, light, motion... etc, which are built depending on their specific requirement. These are battery/solar powered and wirelessly connected for data. Since the sensors are set up in remote open habitats still way off in the distance requirements to be fully reliable and climate-safe. The data is then sent to the cloud-based platform for some more processing and data analysis. This provides for monitoring in real-time and awareness of any environmental changes or abnormalities, making decision-making and task execution more efficient in areas such as agriculture, manufacturing, and infrastructure.

- **IoT Database**

An IoT (Internet of Things) database is a data support system that is designed to power the ever-increasing tide of data produced by connected devices. The database is designed to collect, store, and process IoT data at scale and securely. A distributed architecture to manage the high volumes of data and guarantees data processing and querying with reliability. It is capable of integrating with a huge amount of IoT platforms and apps, making it a very flexible and adaptable database. As such, there is an emerging need for devices to store and access data efficiently, and this is where optimized data structures and algorithms come into play. It also provides real-time data analysis and visualization, which gives businesses and organizations amazing insights.

- **User Input**

User input (or interaction) occurs when you allow users to provide some data in your program, app, or system. This information can be filtered and used to generate an output. The input from the user that enters the processor includes input devices such as keyboards, mice, touchscreens, or voice recognition systems.

The process of attention commences with the calculation of which is defined by equations.

$$g_t = \upsilon^t . \tan x\left(Z_g . x_t + O_g . c_{t-1} + i\right) \tag{12}$$

Where is input, and the soft-max function is used to compute the attention score as follows:

$$j^{t,t} = \frac{\exp\left(g_t\right)}{\sum_{a=1}^{T} \exp\left(g_t\right)} \tag{13}$$

Where each t time was labeled by t.

The context vector is computed as a weighted sum of the Ci. The attention mechanism is described as follows.

$$D_t = \sum_{t=1}^{T} j^{t,t} . x_t \tag{14}$$

The associated long-distance dependencies are constructed per LSTM module output using the attention mechanisms.

Whenever the user enters data, it is converted into a machine-readable representation, which is then stored in a buffer (or memory) until the program uses it. This input is necessary for the programs to work correctly and provides a better user experience by eliciting user input. It also makes the model flexible, as users can benefit from providing different inputs to obtain various outputs.

B. Functional Working Model

- **Crop Knowledge-base Dataset**

The Crop Knowledge-based Dataset is a comprehensive information source about crop planting. This means researchers, farmers, and policymakers can see information on a wide range of crops as they are produced. This database is compiled from various scientific research studies, farming questionnaires, and experts' knowledge. This can include information on varieties, production processes, pests and diseases, harvest practices, and market prices. The data set is regularly updated with development scenarios as agricultural dynamics are modified to ensure the right information is provided to end users at the right time.

Here, *represents the convolution operation, while (15)-(17) represents the capacity of the ConvLSTM architecture.

$$b_t = \sigma\left(Z_{hb}^{*}h_t + Z_{jb}^{*}j_{t-1} + Z_{db}d_{t-1} + i_b\right) \tag{15}$$

$$b_t = \sigma\left(Z_{hp}^{*}h_t + Z_{jp}^{*}j_{t-1} + Z_{df}d_{t-1} + i_p\right) \tag{16}$$

Our operations require the selection, validation, cleaning, and organization of data for this dataset to provide reliable and consistent information. This database is useful for agricultural organizations to inform their decisions and advance farming practices.

- **Crop and Disease Prediction**

Crop and disease prediction is the section that analyses and predicts the possible crop disease and what crop can be grown under the provided environmental and soil conditions. This involves the application of high-tech solutions, where sensors and machine-learning algorithms gather data on temperature, humidity, seed nutrients, soil nutrients, and other factors that influence plant growth. This data is then cross-referenced with historical data and disease patterns to determine possible risk factors and create reliable forecasts. Figure 2 Shows The functional block diagram has shown in the following.

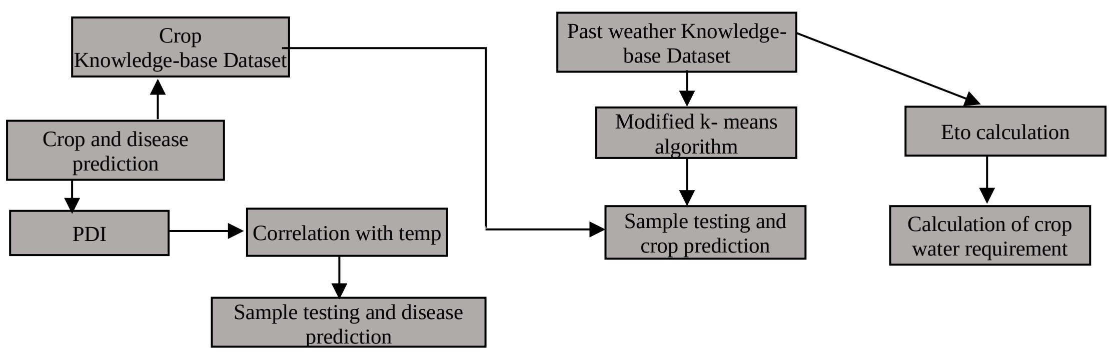

Figure 2: Functional Block Diagram

Those predictions can help farmers determine which crops to plant and how to treat them to stave off or limit infection. This would result in higher crop yields and more efficient use of resources, both of which are important factors for sustainable agriculture.

- **PDI**

PDI (Pentagon Data Integration) is a free, open-source business intelligence tool that enables the performance of ETL (extract, transform, load) tasks, as well as data warehousing. A user-friendly interface for selecting and combining data from various sources, transforming and loading it into the target. The PDI is a visual interface that allows you to transparently drag and drop conditions to constitute data pipelines and projections—advanced features, for instance, job scheduling, cluster mode execution, and data cleaning toolset. PDI modifies data in a process called "transformation," which reads the data and possibly writes it to different locations, transforming it in the process.

- **Correlation with Temp**

Correlation with temperature refers to the statistical relationship between two variables, temperature and a given variable. It involves measuring the strength and direction of the association between these two variables. The analysis is done by calculating the correlation coefficient ranging from -1 to 1. A positive coefficient indicates a positive correlation, meaning that the other variable also tends to increase as temperature increases.

$$x_t = u_t \tan x\left(d_t\right) \tag{17}$$

Also, the corresponding long-term dependence are created via the attention process.

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(\frac{J_t - P_t}{J_t}\right)^2} \tag{18}$$

$$MAE = \frac{1}{m}\sum_{t=1}^{m}\left|J_t - P_t\right| \tag{19}$$

Where the predicted values are represented by and the observed data are represented as ground truth data by.

On the other hand, a negative coefficient indicates a negative correlation, meaning that as temperature increases, the other variable tends to decrease. A coefficient value close to 0 indicates no correlation between the two variables. This information can be valuable in understanding the impact of temperature on the given variable and can aid in making predictions and decisions.

- **Sample Testing and Disease Prediction**

A Vital Aspect of Healthcare is Sample Testing and Disease Prediction Using Healthcare Systems to Find Out Potential Diseases That One Might Have and Give Early Treatments. A sample test requires collecting a biological sample (blood, saliva, tissue) and testing it for the presence of disease-causing agents. To get accurate results, these samples are then analyzed with different methods including genetic sequencing, imaging, or detectable biomarkers. Disease prediction as per these test results and other lifestyle, familial, and environment-related factors helps healthcare professionals to identify people having a risk of contracting particular diseases and offer them personalized preventive interventions. In conclusion, sample testing and a few predictions of diseases are very important for the early detection and management of diseases which contributes to better patient outcomes.

- **Past Weather Knowledge-base Dataset**

The Past Weather Knowledge-base Dataset is a database of historical weather data that offers detailed information on weather conditions in a specific location around the world. It is a data (temperature, precipitation, wind, humidity, air pressure) set, a few different types of data coming from different sources such as weather stations, weather satellites, and buoys. The information is put through special software that breaks the data up into temporal and geospatial order, making historical weather data. All features have undergone minimum-maximum normalisation, with values rescaled between 0 and 1.

$$Q_b = \frac{e_b - \min\left(e\right)}{\max\left(e\right) - \min\left(e\right)} \tag{20}$$

Every node receives a vector, x ∈ RD, as input and produces a scalar in the following way as a nonlinear transformation of the weighted sum of the inputs.

$$w = p\left(i + z^{V} h\right) \tag{21}$$

Where is the non-linear transformation (often a rectified linear unit (ReLU) or tanh), z are the weights, and i is the scalar bias term.

When working with photos, the typical nonlinear function is ReLU. The output that is produced can be shown as

$$W = p\left(i + Z * H\right) \tag{22}$$

Weather forecasters and researchers utilize this dataset to gain insights into long-term weather patterns, identify trends and anomalies, and improve their prediction models. The dataset is continuously updated and expanded, making it a valuable resource for understanding and studying past weather events.

- **Modified k – means Algorithm**

In this case, a k-means clustering algorithm is used (a modification of the original to improve pattern recognition). In this algorithm, the data points are divided into k clusters based on distance and similarity between the data points. The k-means algorithm variant extends the traditional k-means algorithm by incorporating the concept of fuzziness into cluster creation. It reduces the within-cluster sum of squares (WCSS) by updating the centroids of the clusters according to the distance from the data points. This not only decreases the clustering error in general but also explicated clusters whose density is meaningful. The Algorithm recalculates the centroids if their positions are changed and the data points are reallocated to the new centroids based on the dissimilarity with them with each iteration until the convergence criteria are met. This way, we can perform the best clustering and effectively learn from the data.

- **Sample Testing and Crop Prediction**

Sample testing and crop prediction are critical operations in agricultural research and management. Sample testing involves taking small representative samples from a larger population to gather information about the entire population. This is typically done through random sampling, where samples are chosen without bias.

$$w_t = p\left(z_t^{T} h_t + o^{T} w_{t-1}\right) \tag{23}$$

$$k_t = e\left(t^{V} w_t\right) \tag{24}$$

Where the non-linear activation functions are represented by p and e, and the weights given to and are denoted by o and t, respectively.

The forget gate, which determines which data should be removed from the cell state, is described as follows.

$$p_v = \sigma\left(Z_p^{V}\left[x_{v-1}, +h_v\right] + i_p\right) \tag{25}$$

Both of these samples are then used to test for things such as soil health, nutrient levels, and what potentially has infested your plants. This information is commonly used to estimate the condition and potential maximum yield of the crop. A sample of the crop is tested, and by analyzing the data along with other factors, such as weather patterns and market demand, a projection is made on the quantity and quality of the yield to be expected. This information enables farmers to plant and harvest properly and manage the planting process effectively, making the farms more efficient and adopting good agricultural practices.

- **ETo Calculation**

The estimation of evapotranspiration (ETo), i.e., the quantity of water lost per day by transpiration from the vegetation and by evaporation, is derived from the following formula: Eto calculation is a way of estimating water loss through evapotranspiration at a specific point; it is calculated using certain meteorological parameters (temperature, humidity, wind speed, solar radiation). Such estimation is essential for water balances created for a specific area and utilized by various industries, such as agriculture and water resource management.

The input gate that determines the information that should be added to the cell state is defined as

$$b_v = \sigma\left(Z_b^V\left[x_{v-1}, +h_v\right] + i_b\right) \tag{26}$$

The gate that controls which piece of information is added to the cell state is Here.

$$\bar{d}_v = \tan x\left(Z_b^V\left[x_{v-1}, +h_v\right] + i_d\right) \tag{27}$$

$$d_v = p_v^V d_{v-1} + b_v^V \bar{d}_v \tag{28}$$

Eto computation is primarily based on mathematical models and algorithms, with numerous environmental and local factors contributing to the accuracy of Eto estimation. These calculations contributed to informed decisions in water resources management and irrigation methods.

- **Calculation of Crop Water Requirement**

Estimating crop water requirements is a challenging task that involves numerous factors and aspects that must be considered. It is crucial because it enables farmers to determine the exact amount of water their crops require to thrive and produce high-quality yields. The initial part of this process involves determining the crop's evapotranspiration, which is the amount of water needed for the plant to survive and remain healthy. This factor is related to temperature, humidity, wind velocity, and solar radiation. Then, the crop coefficient, which considers the particular water requirements of a crop, is calculated. The calculus also takes into account soil properties, such as texture and water-holding capacity. Finally, the runoff efficiency of the irrigation system is included to estimate the ultimate water required for the crop. This is a useful calculation for farmers, driving water efficiency and waste reduction with direct applications for sustainable crop growth.

C. Operating Principle

- **Input Layer**

The input layer is the first layer in the network, where it receives the input. This layer contains neurons that correspond to the input features from the data. There are connections from every input layer neuron to every hidden layer neuron. These connections have weights (which are adapted during the learning of the network). The input layer is where the raw data is fed into the network, and it has neurons that serve as filters to process the input data. The input layer is crucial for the general operation and learning capabilities of the neural network.

- **Temperatures**

The "Temperatures" function depends on location-based temperature service. The Temperature trievesunction obtains the real-time temperature for the above cities. It functions by using a thermometer to measure the heat energy present in the air. The thermometer consists of a bulb containing mercury or alcohol, which expands as the air temperature rises and contracts when the air temperature falls. This motion of the liquid concerning the glass is itself transmitted to an index, the latter being moved through an angle that bears a numerical relation to the expansion and contraction of the liquid. In present technology, digital thermometers are also available, which display digital readings from electronic sensors on a screen. The "The Temperatures" service serves an essential purpose and can be applied in multiple industries, including agriculture, transportation, and meteorology, allowing for the accurate tracking of temperature changes and assisting in making well-informed decisions.

- **Insecticides**

Insecticides are substances that are meant to attract, seduce and then destroy them. They work by disrupting the normal function of an insect's body or nervous system, causing paralysis or death. The most common type of insecticides are known as neurotoxins, which target the nervous system of insects by binding to receptors and blocking the transmission of nerve impulses. This results in the insect being unable to move or feed, leading to its eventual death. Figure 3 Shows The operational flow diagram has shown in the following.

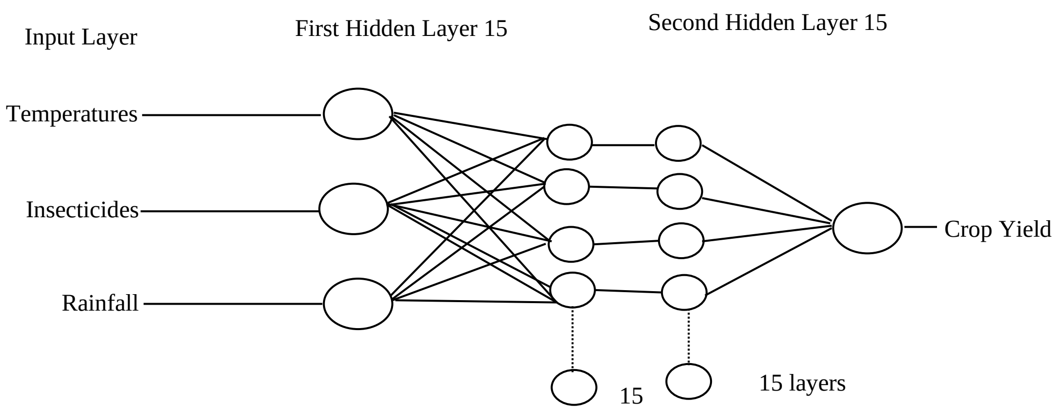

Figure 3: Operational Flow Diagram

Other types of insecticides, such as stomach and contact poisons, work by being ingested or absorbed through the insect's body, causing damage to their digestive system or other vital organs. Insecticides are essential in controlling insect populations and protecting crops from harm. Still, their use must be carefully monitored to avoid potentially harmful effects on other organisms and the environment.

- **Rainfall**

"Rainfall" is a term used to describe the amount of precipitation, or water droplets, that fall from the sky onto the Earth's surface. This natural process is influenced by various factors such as temperature, humidity, and air pressure. Rain formation starts when moisture-laden clouds are lifted into the atmosphere, causing them to cool and condense into tiny water droplets. As these droplets collide and merge with others, they grow in size and eventually become heavy enough to fall as rain.

Similarly, the hidden state x_v and output state u_v of the LSTM are defined as

$$u_v = \sigma\left(Z_u^V\left[x_{v-1}, +h_v\right] + i_u\right) \tag{29}$$

$$x_v = u_v^V \tan x\left(d_v\right) \tag{30}$$

Because LSTM has a more efficient gradient flow during backpropagation, it is more effective than a basic RNN at modelling longer sequences.

The following is the definition of the total loss of the CNN-LSTM network.

$$Loss = \sum_{v=1}^{24}\left(\hat{k}v - kv\right)^2 \tag{31}$$

By applying the L2-loss at every time step, the gradient flow to the shared LSTM weights is increased, leading to faster convergence and better prediction accuracy.

$$MSE = \frac{1}{m}\sum_{b=1}^{m}\left(k_b - \hat{k}_b\right)^2 \tag{32}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{b=1}^{m}\left(k_b - \hat{k}_b\right)^2} \tag{33}$$

The MAE, a measure of errors between paired observations describing the same phenomenon, is defined as the absolute difference between the projected value and the actual value.

$$MAE = \frac{1}{m}\sum_{b=1}^{m}\left|\hat{k}_b - k_b\right| \tag{34}$$

The R^2 (R Squared) is referred to as the proportion of the dependent variable's variance that the independent variables explain. Rain is also important because it helps plants, animals, and people survive. Despite this, excessive or inadequate precipitation can induce consequences for other environmental, agricultural, or social values.

- **Crop Yield**

Crop yield refers to the amount of a crop harvested per unit of land area. It quantifies the degree of efficiency and productivity in agriculture. Estimating crop yield depends on several significant factors, including soil fertility, watering, weather, pests and diseases, as well as the type of crop. For successful crop production, these factors need to be managed by the farmer. Such practices include soil testing and fertilization to achieve optimal soil fertility, the use of efficient irrigation technologies, and effective pest control measures. Moreover, farmers can also choose more resilient crop varieties that are resistant to weather and diseases. In general, crop yield is a key indicator of agricultural production efficiency and significantly contributes to meeting the increasing food demand.

- **Layers**

Layers are a core component of many digital design software, including photo and video editing A layer may be envisioned as a relatively transparent sheet overlaying an altered image or video. This enables components to be focused on individually and combined at the end to form a composite image or video.

Similarly, the hidden state x_v and output state u_v of the LSTM are defined as

$$u_v = \sigma\left(Z_u^V\left[x_{v-1}, +h_v\right] + i_u\right) \tag{29}$$

$$x_v = u_v^V \tan x\left(d_v\right) \tag{30}$$

Since LSTM enables better gradient flow during back propagation, it better models long sequences compared to a standard RNN.

Layers offer non-destructive control over a specific part of an image or video, enabling adjustments without affecting other areas.

Here is the expression of the total loss for the CNN-LSTM network.

$$Loss = \sum_{v=1}^{24}\left(\hat{k}v - kv\right)^2 \tag{31}$$

By using an L2-loss at each time step, favorable gradient flow to the shared LSTM weights is promoted, thereby improving convergence speed and prediction quality.

$$MSE = \frac{1}{m}\sum_{b=1}^{m}\left(k_b - \hat{k}_b\right)^2 \tag{32}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{b=1}^{m}\left(k_b - \hat{k}_b\right)^2} \tag{33}$$

The MAE (the average of absolute errors between paired observations that express the same phenomena) is described as the absolute difference between a projected value and an actual value.

$$MAE = \frac{1}{m}\sum_{b=1}^{m}\left|\hat{k}_b - k_b\right| \tag{34}$$

The proportion of variation (fluctuation) of the dependent variable that can be predicted from the independent variable is called the R2 value.

They can also be repositioned, masked, and modified with a variety of effects and blending modes, providing artists and designers with a high degree of control over their work. Layers are essential for adding depth and a professional touch to your digital design work.

4 Result and Discussion

The model proposed OSDACP has been compared with the existing(option1) Deep Learning Precision Agriculture (DLPA), Option2-Optimized Sensor Data Based Yield Prediction (OSDYP) and Option3-Precision Agriculture Deep Learning Optimized (PADO).

4.1. Accuracy

It indicates how accurately the predictive crop yield analysis model predicts the crop yield. It is usually expressed as a percent yield and can be calculated by dividing the actual yield of a compound by its theoretical yield. Figure 4 shows the Computation of Accuracy Table 2.

Table 2: Comparison of Accuracy (in %)

No. of Inputs	DLPA	OSDYP	PADO	OSDACP
100	57.61	79.16	71.74	80.18
200	57.28	77.66	71.15	78.31
300	55.94	76.55	70.17	77.48
400	54.80	76.17	68.96	76.57
500	53.75	75.16	67.82	75.65

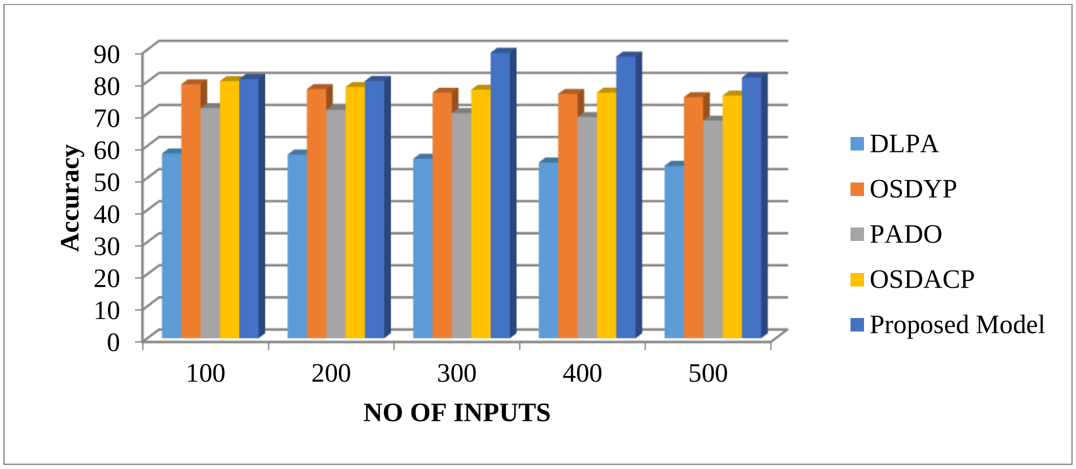

Figure 4: Computation of Accuracy

4.2. Sensitivity

Sensitivity is the model capability of identification and prediction of changes in crop yield by using sensor data variations. A high sensitivity attests that the model can sensitively detect and predict yield changes. Figure 5 shows the Computation of Sensitivity Table 3.

Table 3: Comparison of Sensitivity (in %)

No. of Inputs	**DLPA**	**OSDYP**	**PADO**	**OSDACP**
100	62.61	84.16	77.74	86.18
200	62.28	82.66	77.15	84.31
300	60.94	81.55	76.17	83.48
400	59.80	81.17	74.96	82.57
500	58.75	80.16	73.82	81.65

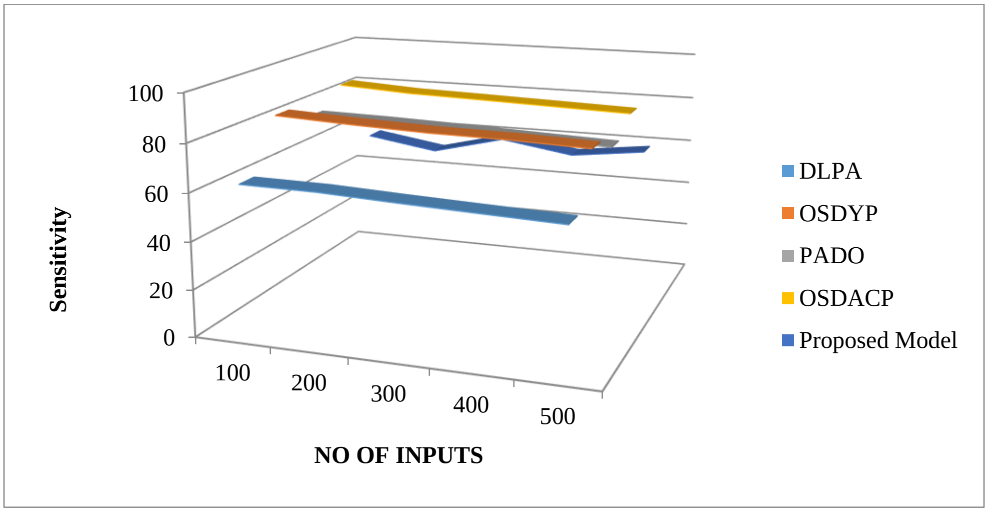

Figure 5: Computation of Sensitivity

4.3. Speed

The running time of the predictive analysis model for crop yield is a crucial technical performance parameter. A rapid and efficient model can process more sensor data relatively quickly, leading to timely and accurate predictions. Table 4 compares the proposed and existing methods for Speed Figure 6.

Table 4: Comparison of Speed (in %)

No. of Inputs	DLPA	OSDYP	PADO	OSDACP
100	65.61	90.16	81.74	89.18
200	65.28	88.66	81.15	87.31
300	63.94	87.55	80.17	86.48
400	62.80	87.17	78.96	85.57
500	61.75	86.16	77.82	84.65

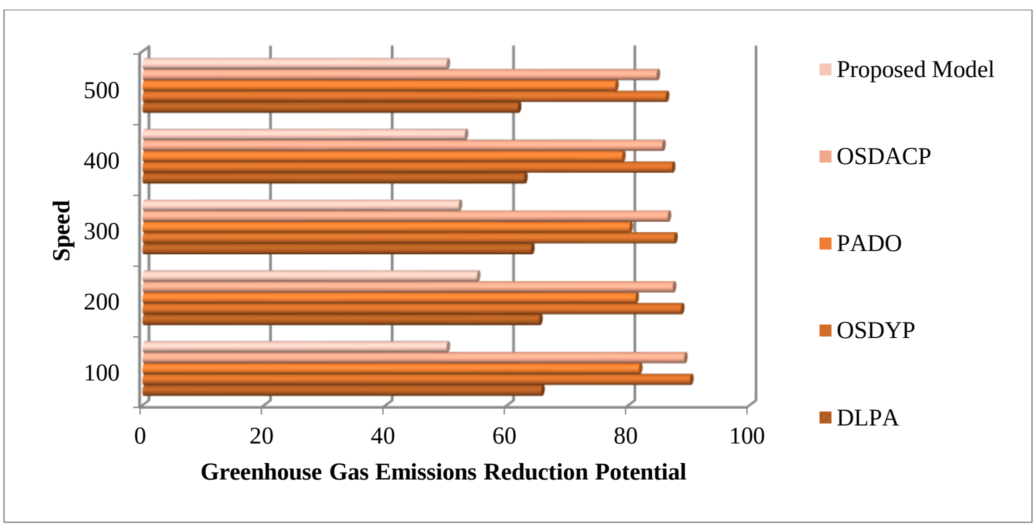

Figure 6: Computation of Speed

4.4. Robustness

Robustness is the capacity of the model to deliver good results even when the input data contains variations or disturbances, such as variations in weather conditions or unexpected changes in crop growth. A strong model will remain challenging to predict despite these conditions. Table 5 presents a comparison of Robustness for the existing and proposed models. Figure 7 shows the Computation of Robustness**. (**Table 5)

Table 5: Comparison of Robustness (in %)

No. of Inputs	DLPA	OSDYP	PADO	OSDACP
100	71.61	96.16	83.74	96.18
200	71.28	94.66	83.15	94.31
300	69.94	93.55	82.17	93.48
400	68.80	93.17	80.96	92.57
500	67.75	92.16	79.82	91.65

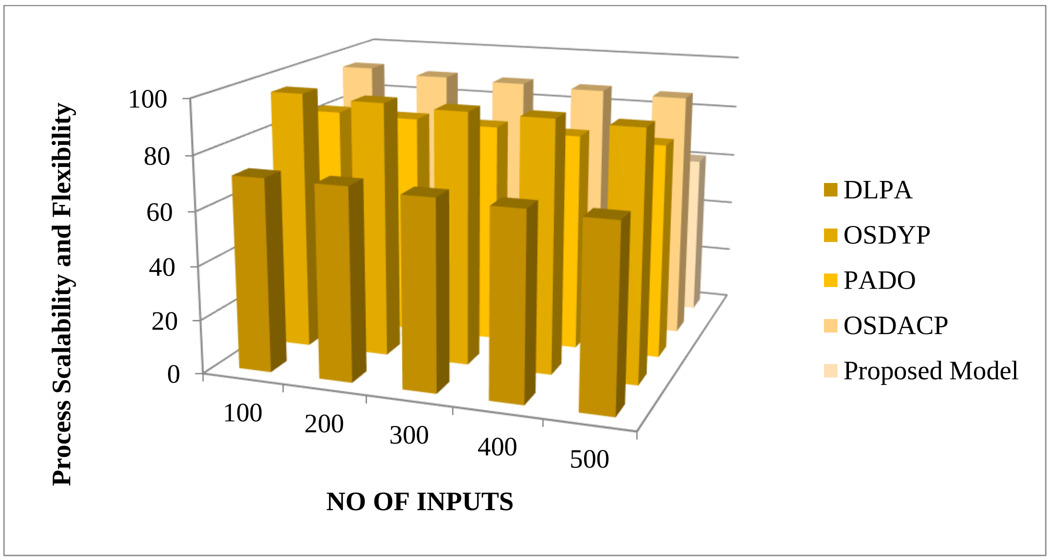

Figure 7: Computation of Robustness

5 Conclusion

Deep learning and sensor data adjustment in precision agriculture may be a potential avenue to predict farm yield." Machine learning techniques, such as convolutional neural networks and random forests, have enabled us to forecast with greater precision and far earlier in human history, providing farmers with a means to hedge risk and farm more sustainably. That could be a productivity boost that saves money for farmers and promotes more sustainable approaches to agriculture, which in turn could help reduce water and fertilizer use. Furthermore, sensors and drones are employed as systems to create in-situ surveillance in real-time, gathering data for more informed applications on the health and progress of crops. This will be an essential tool in the future of agriculture, enabling high-throughput predictive crop yield analysis with deep learning on realistic sensor data for precision agriculture as technology advances.

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