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Design and Implementation of a Cloud-Based Smart Agriculture System for Crop Yield Prediction using a Hybrid Deep Learning Algorithm

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Abstract

This article proposes a cloud-based smart agriculture system for crop yield prediction using hybrid deep learning techniques. The study aims to improve crop yield prediction accuracy and facilitate decision-making for farmers. The system utilizes a hybrid deep learning approach that combines convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to process multi-sensor data, including weather data, soil moisture data, and crop growth data. The CNNs are used to extract spatial features from the input data, while the RNNs are used to capture temporal dependencies. The proposed model is employed on a cloud platform, allowing farmers to access the system from anywhere using a web-based interface. Experimental results show that the proposed hybrid deep learning approach outperforms traditional machine learning methods for crop yield prediction, achieving a prediction accuracy of over 90%. Its ability to predict crop yields properly was demonstrated by its decreased MAE and RMSE to 2.17% and 2.94% respectively. It also showed a better fit between the expected and actual data, with a higher R-squared value. The proposed system has the potential to improve the efficiency and profitability of farming operations and contribute to sustainable agriculture practices.

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Cloud-Based Smart Agriculture; Containers; Convolutional Neural Network; Crop Yield Prediction; Deep Learning; Internet of Everything; Image Processing.

Introduction

The Internet of Things (IoT) could be a game-changer for people and the world as a whole in many ways.[1] Extreme weather, soil erosion, drought, and the collapse of ecosystems are making it harder and costlier than ever to grow food. But our number of people is not in any way going down. A widely used prediction says that by 2050, the world's population will be more than 9 billion. The good news is that there is still reason to be hopeful because technology and Internet of Things apps for smart farming are improving quickly.[2] Experts predict that this industry will be worth a whopping $23.14 billion by 2022 and that 75 million IoT devices will be used in farming

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over the next few years. The Internet of Objects is based on connecting "dumb" things to the web and each other. The goal is to turn "dumb" things into "smart" ones. By letting computers sense and move objects from a distance, it makes it easier for digital and physical systems to work together.[3,4] In the Internet of Things, sensors built into Internet-connected objects make it possible for them to talk and interact with each other. With today's technology, everything from pumps and barns to tractors, weather stations, and even laptops can be managed and watched in real time from afar. In some places, like India, agriculture is the only industry that helps make food. It's a successful business, but the number of people who work there has been steadily going down over the years.[5] When traditional farming methods try to make their crops more productive, they face a lot of problems. Problems in rural areas are made worse by things like global climate change, pollution, the inability of damaged soil to support crop growth, rapid urbanization, and the loss of farmland. Figure 1 shows how smart farming practices can help farmers get more crops and make more money.[6] Also, these new farming methods, along with traditional farming, will need technical support to meet the world's food needs effectively. To deal with these problems, it is important to use modern farming methods like hydroponics, vertical formation, and polyhouse.[7,8] Hydroponics is the most successful of these methods because it meets the needs of technology head-on.

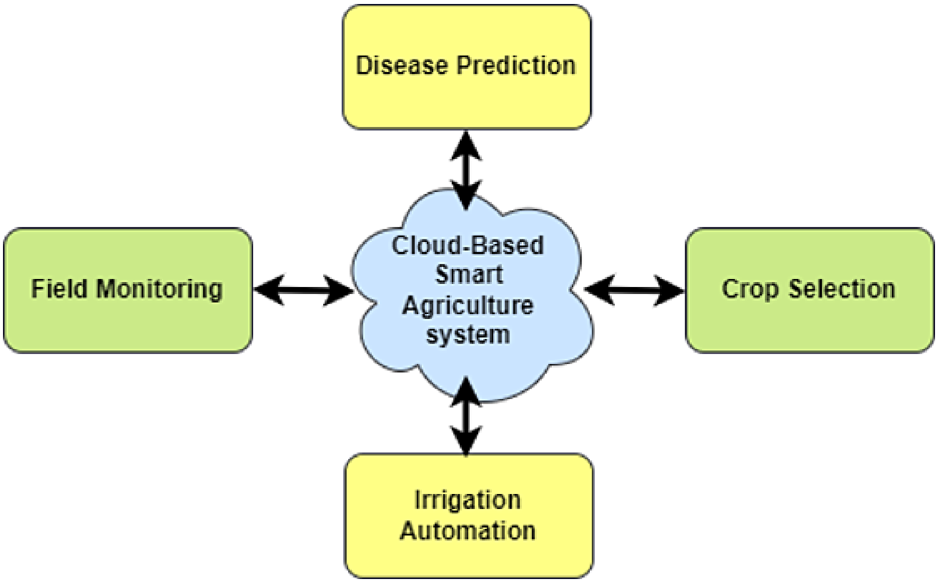

Fig. 1: Cloud-based model for Smart Farming

When a plant starts to wilt, it becomes less stiff and its leaves start to dry out. Wilting can be caused by many things, but lack of water and too much heat are the most common.[9] The roots of a plant can die for several reasons, such as when the water is too hot, when the EC is too high or too low, or when the soil is too dry. If there are rotten roots, that means there is a pathogen in the system that causes root rot. Many people agree that clogging is the most common problem with hydroponic systems, and this is especially true for those who use a drip-style irrigation system. Most clogged tubes are caused by pieces of the growth medium. When there is a blockage, the flow of the whole system is messed up, which could be very bad for your plants. No matter how well farmers take care of their hydroponic plots, there is always a risk of infection. This is true even when everything is going great. At the start of an infestation, there are some things you can do to try to get rid of the problem. During the early stages of an infestation, you can take certain steps. Before deciding that there is a problem, In the last few years, most plant care tasks in hydroponics have been taken over by autonomous robots powered by artificial intelligence (AI) and equipped with a wide range of hardware controllers and industrial robots.[10] But they couldn't figure out how to monitor a lot of sensors at the same time to solve the problems that were already mentioned. Both traditional farming and hydroponics can be hurt by plant diseases, which is another big problem. When plant diseases spread, they slow down the growth of plants and make it so that less food can be harvested. Usually, farmers or pathologists classify illnesses by hand, and pathologists then use lab tests to figure out what's wrong. There are pros and cons to both of these ways of doing things. Traditional systems, on the other hand, can only work as well as their level of experience allows,[11,12] which is hard and takes time. Early detection and prevention of plant diseases can also help hydroponics work better. Because of this, many computer-aided methods based on image processing have been widely developed in recent years to help farmers. This is why image-processing technologies are used for early detection and diagnosis.[13] This study discusses the application of artificial navigation systems for autonomous vehicle navigation. The techniques rely on machine vision technologies to extract feature points from images taken by vehicle-mounted cameras. Vehicle self-positioning is estimated by artificial intelligence algorithms using these photographs. Autonomous vehicle navigation is made possible by the knowledge of vehicles' self-position. The techniques are efficient, and cars are driven through congested areas.[19] A created 2D-CNN was fed the extracted data set of images for classification, and its performance was further evaluated using F1-score, AUC-ROC, accuracy, precision, and specificity. In most of the classes of unifloral honey variations used for categorization, the AUC-ROC value was greater than 0.98. The acquired results showed that this experimental strategy performs better than the current algorithms used to evaluate food quality features when combined with the created 2D-CNN model. From this point forward, the industry and consumers of honey would both profit from this innovative method of honey authentication; additionally, it motivates researchers to take advantage of this application of hybridized technology in food quality assurance and control20 To reach this goal, color feature extraction, texture feature extraction, and shape feature extraction are all used. Here are the most important ways that these works have helped us understand and deal with these issues better:

(i) The creation of an AI-powered SHES that uses a Raspberry Pi controller, an Internet of Things (IoT) ecosystem, and a mobile app.
(ii) The Agri-Hydroponic program helps farmers keep track of and manage their hydroponic farm fields. It has an easy-to-use interface for farmers who want to use it.
(iii) Make a cloud-based IoT infrastructure for monitoring sensor data all over the world.
(iv) Also, an AI framework has been made to look at sensor data and plant diseases so that alerts can be sent and predictions can be made.

Related Work

This section discusses the recent developments proposed by various authors in the field of smart agriculture. The rapid growth of cloud computing has led to the creation of many MLaaS platforms. Training and development of machine learning models are done in the environment provided by cloud service providers. However, this could cause privacy and security problems because deep learning algorithms need access to the data collection that was made, which is inherently dangerous. For example, the second one might help the first one. The main goal of this research is to come up with a plan for the safe design of a deep learning system by looking at the risks that come with smart farming applications. This is because more and more people are interested in these technologies to help meet the growing need for food around the world. This is why we chose to focus on this study. Smart farming, also called "precision agriculture," is the process of maximizing crop yields and food quality by using data-driven technology in agriculture. In the past few years, many examples of how "smart farming" can be used to increase agricultural output have come to light.[1] "Precision agriculture" (PA) is a management term that refers to the practice of using data and communication technologies in farming. The only way to increase output is to use the best farming methods and get the most out of all the inputs. Some of the problems that the agricultural industry is facing right now are soil degradation, climate change, and rising prices. Despite these problems, Pennsylvania uses Wireless Sensor Networks (WSNs) to collect, share, and make sense of data to improve agricultural output. PA also gets help from many different technologies from different fields as it looks for new ways to use them. Since they were first made, ML and AI have had a big effect on almost every part of PA. By moving processing to the edge of the network, where it is used, the fog/edge paradigm is helping to solve many problems, such as those with network capacity and security. Software-defined networks (SDN) make networks more flexible; Big Data makes it easier to process data, and nanotechnology has a big impact on fostering innovation in PA. As a result of all of these technological developments, Pennsylvania has become a leader in innovation. The article looks at how these technologies are changing PA in their fields and shows why PA needs to use approaches from different fields to grow in the future. This research gives a full picture of the situation and suggests a multidisciplinary architecture called Agri-Fusion that aims to make agricultural solutions more effective and affordable. The article talks about a few commercial ways to handle different parts of farm management and the technology behind them. It's possible that this would make it easier for PA to work on both academic and business goals at the same time. The article also breaks down systematically how the performance gap between available resources and PA goals can be described. Also included is a recommended solution architecture for building KPI in PA. At the end of the talk, we talked about several open research questions about how PA is used and what its long-term goals are.[2] In India, agriculture is the main source of income and jobs. Agriculture and irrigation are the most important and important parts of the world's economy as they are now. We need to use information and communication technology in our agricultural businesses so that we can help farmers and agriculturalists increase crop yields during the whole process of growing crops and after they have been harvested. When this happens, the GDP of the country goes up. Farming can't reach its full potential without the help of many kinds of modern technology. The changes in technology over the last few decades have helped the agricultural industry a lot. Researchers have been able to use this automation in agriculture to help farmers because of progress in the Internet of Things (IoT) and machine learning (ML).[3] In this article, the author talks about the results of a study that looked at how deep learning could be used to automate the process of figuring out what kind of disease is affecting a vine leaf. Syria and its neighboring countries, like Turkey, have been growing grapes and other fruits that grow on vines for a long time. Grapes and other fruits that grow on vines have a special cultural meaning in Syria. Grapes are a staple in the diets of people in these areas, and they are also very important to the local economy. This means that the grapes used in production must be of the highest quality possible.[4] As the number of connected devices grows, so does the amount of information that needs to be processed, analyzed, sent, and stored in the cloud. This means that the way information is organized and managed needs to change. There are two suggestions for how to solve the problem.[5] When soil moisture levels fall below a certain threshold, they activate automated watering; otherwise, the irrigation process is stopped until soil moisture reaches the appropriate level. The sensors take measurements of the surrounding conditions every few minutes. For analysis, information is gathered and kept on a Thing-Speak cloud server. They employed a range of models, including random forest, logistic regression, K-nearest neighbors (KNN), and Naïve Bayes, to assess the data we gathered. The accuracy rate was 91.8%, the mean square error was 0.16, and the outcomes of logistic regression, KNN, and SVM were (91.3%/1.66), (92.3%/0.66), and (92.5%/0.5), respectively, in comparison to other Naïve Bayes and random forest models. Ultimately, an IoT-powered smart irrigation system provides farmers with access to.[7] To lessen costs and labor, this study offers and implements a cloud computing architecture for hybrid Arabic text tagging. The outcomes demonstrate a very high rate of accuracy in Arabic text tagging and prompt response.[14] In this paper, the author first discussed the importance of smart agriculture practices with the growing gaps in global food demand versus current food generation, the growing shortage of arable land for agriculture, stricter regulations by international organizations on the use of toxic pesticides/herbicides, and global shortage of water resources for irrigation purpose. All of the challenges cannot be met through traditional agricultural practices. We then discussed in detail the current hardware building blocks of the smart agriculture system, which is primarily based upon a large number of IoT nodes deployed in the field with suitable sensors to monitor the current situations of crops. The monitored parameters are transmitted wirelessly through various available technologies for the farmer to take remedial actions manually or automatically.[15] The effectiveness and caliber of the teaching and learning process are improved by smart e-learning. An alternate option for institutions trying to manage or improve their IT resources more efficiently and stay up to date with the latest developments in information and communication technologies is a smart e-learning system. It lowers the operational expenses of IT while also offering a means of providing more affordable, safe, and dependable educational services. To provide and share e-learning resources, the research article explored the conventional e-learning system and suggested a smart e-learning system based on cloud platforms. The authors presented the design of a smart e-learning system for educational institutions and talked about the advantages of this system over traditional ones.[16] Due mainly to disregard for applying K through fertilizer or other sources, the K balance remained predominantly negative for a considerable amount of time in the majority of Indian states and all major agricultural systems. Indeed, K mining has been going on continually in India's heavily farmed soils. Long-term, continuous K mining can deplete different K pools, particularly the exchangeable and non-exchangeable pools, which could hurt soil fertility and general health. Furthermore, prolonged soil K mining may result in permanent alterations to the minerals that contain K. Collectively, these present a possible threat to the sustainability of agriculture. The current K fertilizer recommendations for large agricultural systems have repeatedly shown themselves to be inadequate and require adjustment. There have been attempts to incorporate parameters about non-exchangeable K, quantity intensity, release-fixation, etc.[17] Authors address this difficulty by taking partial overlap range scans at many locations in addition to GPS data. With the help of a quick and enhanced ICP method, the range images are aligned in the local coordinate system. The transformation between GPS location estimations and aligned scan centers is estimated using GPS data at chosen positions with a high likelihood of position correctness. Locally aligned 3D points are transformed into world coordinates using the acquired transformation. The accuracy of the global alignment is confirmed by an evaluation based on the orientation of building facades, positioning on aerial pictures, and overlapping of surrounding regions, among other factors.[18] The main goal of the first, multi-cloud computing, is to ensure redundancy so that latency can be improved. The second option is the Federated Cloud, which brings together all the resources to make the most of them. Table 1 discusses major contributions and techniques used by authors for Crop-Yield Prediction.

Table 1: Comparative analysis table for Crop-Yield Prediction using hybrid deep learning.

Methods	Dataset	Evaluation Metric	Results
CNN-LSTM7	Indian Agriculture Dataset	RMSE	1.84
ResNet-LSTM8	Indian Agriculture Dataset	R^2	0.97
Autoencoder-GRU9	Soybean Dataset	R^2	0.94
MLP-CNN-LSTM10	Wheat Dataset	R^2	0.96
LSTM-ConvLSTM11	Tomato Dataset	MAE	0.28

Cloud-Based Architecture

Cloud Paradigm

As the number of connected devices grows, so does the amount of information that needs to be processed, analyzed, sent, and stored in the cloud. This means that the way information is organized and managed needs to change. There are two suggestions for how to solve the problem. The main goal of the first, multi-cloud computing, is to ensure redundancy so that latency can be improved. The second option is the Federated Cloud, which brings together all of the resources to make the most of them.

Multi-Cloud Computing (MCC).

A type of cloud computing where services are spread out across many clouds. In this architecture, the whole workflow is done in the cloud, and data redundancy is also checked. The MCC has a high rate of recovery, but it also has some of the problems of cloud computing, like being hard to understand and hard to move around.

Federated Cloud (FC).

It brings the power of many cloud providers together, giving users more freedom to choose which service to use and where to host their apps. One way to think of a federated cloud is as a loose group of independent clouds that have joined forces to share their extra resources. By cloud federation, service performance can be kept up even when more people are using the service. This is done by borrowing resources from other clouds.[21,22] With multiple locations around the world, it's also easy to switch to a different node if one goes down and keep the service going. With an easy-to-use interface, customers can quickly find out what services are available. Because the load is spread out in a different way for each user, the treatment can be moved closer to the user, which improves QoS. The European Cloud and the Open Cloud in Massachusetts are both examples of clouds that are linked together.

Distributed Architectures

Post-cloud solutions might help reduce latency and jitter for things that stay in one place, but they don't work for mobile devices that are aware of their surroundings. The exponential growth of data production at the network's edges is causing the speed of data transit to go up, which is becoming a bigger problem for cloud-based computing.[23,24] When using the cloud to store and process data, there are no guarantees that the data will be kept private, that response will be quick, or that they will be made in real-time. Because there are so many devices, both latency and jitter have to be better. Also, it's always hard to talk to the cloud because devices are always moving and there's never enough power.[25] By putting data storage and processing closer to the devices that create data, the goal has been to cut down on bandwidth use and make the cloud less busy. This includes sorting the data and figuring out what it all means. Several fundamental paradigms have been suggested as ways to solve these problems, bringing cloud-like computing to the edges of the network. Each of these systems controls how Virtual Machines (VMs) or containers move between hosts and, if necessary, changes how services are delivered based on where users are. As a bonus, these three models make it possible to build federated infrastructures, which have many edge infrastructures that can talk to each other and share resources.[26] Sustainability in agriculture has worked well in several places. In "smart agriculture," on the other hand, the use of deep learning has gone mainstream, leading to sophisticated and pleasant manufacturing results. The purpose of this study is to look at and analyze deep learning techniques and how they might be used in agriculture. This will give researchers a resource that is both complete and up-to-date.

This survey is made up of three main parts. The first step was to look for relevant keywords to get the needed information (agriculture, deep learning, convolutional neural networks, recurrent neural networks, crop monitoring, disease detection, and irrigation systems). We used keywords to look for journal and conference papers in the scientific. After reading all of these articles, we cut the number of possible choices down to forty. All of these studies did deep learning experiments and wrote up what they found. In the second step, the chosen scientific articles were compared and contrasted based on the following criteria:

The areas of smart agriculture that were focused on.

- Because of those problems, they had to look for answers.
- They used methods and models based on deep learning.
- An explanation of the data set that was used.
- The ways that the data for this study were cleaned up and added to.
- How precise or accurate the results are.

In the third and final phase, we tried to find solutions to problems that all of the publications we looked at had in common. Based on the results of this study, we came up with a new type of deep learning model that combines CNN and SVM to make existing models more accurate and precise.

Deep Learning for Smart Agriculture

Deep learning algorithms are used in smart agriculture to keep track of a large number of connected metrics that can all be seen from anywhere in the world. Our most recent polls show that most people want to know more about how deep learning can be used in agriculture. Throughout this report, we've talked about the different ways that deep learning has made smart agriculture better. We tried to find out which deep learning model is the most useful and successful overall, as well as which one is best for certain uses. Academics are becoming more interested in using CNN algorithms to identify and classify plant diseases because they have worked so well in the past. Because of the amazing results this method has brought.

The CNN algorithm is also often used to predict the weather because it is based on time series and gives accurate results. Both the many specializations of "smart agriculture" and the uses of "deep learning" were looked into.

When the fungus, germs, and bacteria that cause plant diseases get their food from the plants they infect, crop yields can go down. If the problem is not found and fixed quickly, it can cause farmers to lose a lot of money. Even though farmers need to use pesticides to get rid of pathogens that hurt crops and get crops to work again, this costs them a lot of money. Pesticides hurt the environment and mess up the water and soil cycle in farming communities when they are used too much.[14] Also, some plant diseases slow down the growth of these plants, so it's important to find stress early. There have been many different deep learning (DL) models used to find and name plant diseases. Consistent use of deep learning seems to hold a lot of promise for improving accuracy in the future. In the literature, there are many ideas for both brand-new DL architectures and improvements to the ones that are already out there. A wide range of high-level visualization techniques is used in the current ways to recognize and classify plant disease symptoms.

A way to find and name diseases related to bananas is based on the Convolutional Neural Network model. Farmers could benefit from using it if it helps them figure out what kind of disease they have quickly, cheaply, and correctly. This system was able to tell the difference between Sigatoka banana fungus and speckle banana fungus by using a model based on deep neural networks to look at a photo of a damaged leaf. The authors of the study[17] used pictures of diseased plant leaves and another deep-learning network called AlexNet to figure out what kind of disease was affecting the plants. The results were exactly right. In,[18] there is an article that talks about a hybrid deep-learning model for classifying diseases in sunflowers. Among them are diseases such as Alternaria leaf rot, Downy mildew, phoma rot, and verticillium wilt. The author made a hybrid model that combines H.VGG-16 and MobileNet by using the stacking ensemble learning method. They used Google Photos to help build their dataset, and they said that the 89.2% accuracy of the model they suggested was better than what had been done before.

Proposed Model

Data Collection

The first step is to collect data from various sources, including weather data, soil data, and crop data. Dataset The crop prediction model is trained on a dataset that contains information about, including their soil and climate conditions, and yield potential. The dataset also includes historical weather and soil data for different regions. The model uses this data to predict the yield potential of different crops in a given area based on the current climate and soil conditions. The dataset is collected from data world, Soyabean Large dataset from UCI Machine Learning Repository, Indian Agriculture Dataset, which almost covers all the states of India. This dataset is crucial in training and evaluating the crop prediction model’s accuracy.

Soyabean large data set is a categorical multivariate dataset containing thirty-five features and 307 instances. The dataset is categorized into 15 different classes.

Hybrid Deep Learning Model

The hybrid deep learning model consists of two main components: a convolutional neural network (CNN) and a long short-term memory (LSTM) network. The CNN is used to extract features from the input data, while the LSTM is used to capture temporal dependencies in the data.

Input Data

The input data to the hybrid deep learning model consists of a sequence of weather, soil, and crop data over a specified period. The input sequence is denoted by X = $\{x_1, x_2, ..., x_n\}$, where each xi represents the input data at time i.

Feature Extraction

The input data is passed through the CNN to extract features that are relevant to the crop yield prediction task. The output of the CNN is a sequence of feature maps denoted by F = {f1, f2,...,fn}, where each fi represents the features extracted at time i.

Temporal Modeling

The sequence of feature maps is then passed through the LSTM to capture the temporal dependencies in the data. The output of the LSTM is a sequence of hidden states denoted by H = {h1, h2, ..., hn}, where each hi represents the hidden state at time i.

Crop Yield Prediction

The final step is to use the output of the LSTM to predict the crop yield. This is achieved by passing the sequence of hidden states through a fully connected layer with a softmax activation function to obtain the predicted crop yield. The predicted crop yield is denoted by Y = {y1, y2, ..., yn}, where each yi represents the predicted crop yield at time i.

Training

The hybrid deep learning model is trained using a labeled dataset and an optimization algorithm, such as stochastic gradient descent. The model's weights are adjusted to minimize the difference between the predicted crop yield and the actual crop yield.

Prediction

Once the model has been trained, it can be used to make predictions on new, unlabeled data. The input sequence of weather, soil, and crop data is passed through the trained model to obtain the predicted crop yield.

The algorithmic approach provides a powerful and efficient way to predict crop yield using hybrid deep learning techniques.

The equations for the combined CNN and RNN model can be summarized as follows:

Convolutional Layer

$$Ci = ReLU(Wi * Xi + bi) \quad ...(1)$$

where Ci is the output feature map, Wi is the convolutional filter, X^i is the input data, and bi is the ith term.

Pooling Layer

$$Pi = max (Ci) \quad ...(2)$$

where Pi is the output of the pooling layer, and Ci is the input feature map.

Recurrent Layer

$$Ht = f (Wx * Xt + Wh * Ht\text{-}1 + bh) \quad ...(3)$$

where Ht is the hidden state vector at time t, Wx is the input weight matrix, Xt is the input data at time t, Wh is the hidden weight matrix, Ht-1 is the previously hidden state vector, and bh is the bias term.

Fully Connected Layer

$$Z = ReLU (Wf * Ht + bf) \quad ...(4)$$

where Z is the output of the fully connected layer, Wf is the weight matrix, Ht is the input data, and bf is the bias term.

Output Layer

$$Y = Wout * Z + bout \quad ...(5)$$

where Y is the predicted crop yield, Wout is the weight matrix, Z is the input data, and bout is the bias term. Overall, the combined CNN and RNN model for crop yield prediction is a powerful tool for agricultural analysis and can help farmers make more informed decisions about crop management and planning.

Classification and Combination

For each IMF in the frequency domain, one-dimensional convolution operations are done to show how the different frequency components work together. Here is the formula for the convolution:

$$(x) * g(x) = \int_{-\infty}^{+\infty} f(\tau) * g(x-\tau)d\tau \quad ...(6)$$

where g is the convolution kernel function and f(x) is the function that has been messed with (x). Using a Gaussian kernel function g(x), the result of a one-dimensional convolution is equal to the integral of the integrand function f(x)*g(x) on the interval (,+). (x).

IMF-0 can cover a much wider range of frequencies. IMF-1 and IMF-2 have both shrunk a lot, but their tails are still quite long inside the cut-off frequency range. When compared to IMF-3 and IMF-4, this model's slope goes down more quickly, which shows that fewer frequency components are being taken into account. Also, we see that the changes in these components on the map of the time domain are pretty flat, and the slope down for IMF-5–8 is almost vertical.

We use the CNN neural network to classify and sort IMFs because the convolution operation can track how the data changes over time. To figure out what IMF sequences are about, a one-dimensional convolutional neural network (CNN) is used. Using the convolution kernel function and an input IMF sequence called Xt, where t can range from 1 to n, the filters perform a local convolution operation on the input features of the layer below them in order. The convolution could lead to something like the picture below.

$$x_t = \sum_{l=1}^{m} k_l \times X_{t-l+1} \quad ...(7)$$

This paper tells why the fast-convergent rectified linear unit (ReLU) was chosen as the activation function.

$$f(x_t) = \begin{cases} 0, & x_t \leq 0 \\ x_t, & x_t > 0 \end{cases} \quad ...(8)$$

Then, using flattening and full connection techniques, a one-dimensional CNN is used to get the frequency characteristics of the IMFs. Then, the Softmax classifier sorts the traits into groups, and the network's output is found (i.e., the labels for each IMF). The model for the easy-to-understand cable news channel.

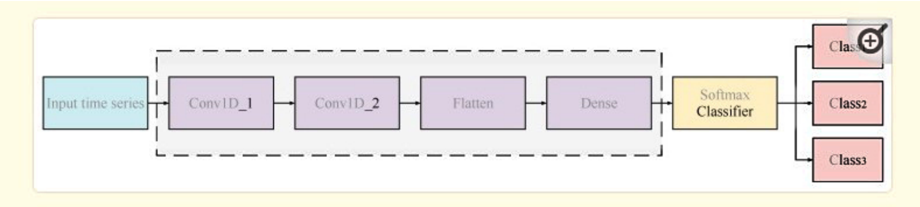

Fig. 2: Putting together a convolutional neural network in one dimension (CNN).

Results Analysis

By using data from earlier tests to fine-tune the hyper-parameters, a deep neural network representation was made that was both accurate and fast. The startup phase of the deep learning network was started with Keras's default settings (e.g., weight initialization). The ReLU function is the way that the CNN models turn on. On two levels of convolutional processing, the CNN used 32 convolution kernels and a logistic loss function. The size of the kernel was found to be 5. Both what went into and came out of the CNN were 24. A one-hot method was used to code the labels that were used to identify people.

Before building began, the number of neurons in the GRU was set at 24, and it stayed at that number throughout. GRU uses the Adam method to get accurate prediction results because the IoT system will almost always add noise to the sensor data. To reach this goal, a specific function is optimized to its highest possible value. Huber loss is another idea that is used. To make the sub-predictive models, a GRU was used to train the subsequences. Tanh, which is the GRU activation function, is used in both cases. In the tests, we looked at the forecast for the next day as if it were 24 hours away. We used the weather information from the day before to make the forecast for the next day. That is, we made plans for the next 24 hours based on what we knew from the day before.

In Cases 1 and 2, the difference between what was predicted and what was seen was measured by the root mean square error (RMSE). The equation shows that there is a difference.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_{pre}(i) - x_{obs}(i))^2}{N}} \quad ...(9)$$

where N is the number of datasets used to make a prediction, xobs stands for "observed data," and "xpre" is the value that was predicted.

Mean Absolute Error (MAE) is a measure of the average size of the mistakes in a collection of predictions, without taking their direction into account. It is measured as the average absolute difference between the predicted values and the actual values and is used to assess the effectiveness of a regression model.

$$MAE = \frac{\sum |predicted\ values - observed\ values|}{number\ of\ items} \quad ...(10)$$

R-squared (R^2) represents the goodness of fit of a regression model. The value of the R-square lies between 0 to 1. Where we get R-square equals 1 when the model perfectly fits the data and there is no difference between the predicted value and actual value. It is unit less entity.

R^2= 1-(Sum of square of residuals)/(Total sum of squares) ...(11)

where residual is the difference between observed and predicted values. Range of R-squared (R^2) is between 0 to 1.

The study on the design and implementation of a cloud-based smart agriculture system for crop yield prediction using hybrid deep learning might be analyzed with a table

Table 2: Comparison of Crop Yield Prediction Results using Different Deep Learning Models.

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R-squared (R^2)
Hybrid Deep Learning	2.17%	2.94%	0.83
Convolutional Neural Network (CNN)	3.25%	4.67%	0.67
Recurrent Neural Network (RNN)	2.81%	3.88%	0.74
Decision Tree (DT)	3.11%	3.97%	0.69
K-Nearest Neighbors (KNN)	2.98%	3.67%	0.71
Modified Deep Learning Strategy (MDLS)	2.78%	3.12%	0.78

Table 2 shows the results of a study that compared the performance of three different deep learning models for crop yield prediction: a hybrid deep learning model, a convolutional neural network (CNN), and a recurrent neural network (RNN). The mean absolute error (MAE), root mean square error (RMSE), and R-squared (R^2) were used as evaluation metrics.

As seen from the table, the hybrid deep learning model outperformed the other two models in terms of all three metrics. It achieved a lower MAE and RMSE, indicating that it was better able to accurately predict crop yields. Additionally, it had a higher R-squared value, indicating a better fit between the predicted values and the actual values.

Overall, these results suggest that the hybrid deep learning model is a promising approach for crop yield prediction in smart agriculture systems. By combining the strengths of both CNNs and RNNs, the hybrid model was able to leverage the spatial and temporal features of crop data to improve prediction accuracy.

Conclusion

Crop yield prediction using deep learning is a promising area of research that has the potential to revolutionize the agriculture industry. Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have shown impressive results in predicting crop yields based on various inputs such as weather data, soil information, and satellite imagery. These models can learn complex patterns and relationships from large datasets, allowing for more accurate and reliable predictions. However, there are still some challenges that need to be addressed to fully realize the potential of deep learning for crop yield prediction. One of the main challenges is the availability and quality of data, particularly in developing countries where data collection and management systems may not be well established. Another challenge is the interpretability of deep learning models, as they are often considered to be "black box" models that are difficult to understand and explain. Despite these challenges, there is great potential for deep learning to make significant contributions to crop yield prediction and agriculture as a whole. In the future, further research can be conducted to address the challenges mentioned above and explore new techniques and architectures for deep learning models. Additionally, efforts can be made to develop user-friendly interfaces and tools that allow farmers and policymakers to access and interpret the predictions generated by these models. Overall, the use of deep learning for crop yield prediction is an exciting and rapidly evolving field that has the potential to bring about significant improvements in food security and agricultural sustainability.

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No potential conflict of interest was reported by the author(s).

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The soyabean data set is downloaded from UCI KDD dataset available at DOI: 10.24432/C5JG6Z.

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Not applicable

Authors' Contribution
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