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# Crop Yield Prediction using Hybrid ANN-CNN Algorithm

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**Abstract**: Crop management is very important function to improve the quality of the crop. Nowadays drones are playing a vital role in crop management function of agriculture like crop monitoring, scanning of fields and so on.

**Keywords**: Crop Management, Algorithm, Hybrid ANN-CNN.

## I. INTRODUCTION

The application of machine learning in crop yield prediction has revolutionized decision support in agriculture sectors worldwide. As this technology enables computers to learn from vast amounts of data without explicit coding instructions, it is a particularly effective solution for managing large datasets with ease. Many machine learning algorithms are available that cater specifically to crop yield prediction research purposes as well as provide predictive insights based on critical variables like rainfall or temperature. These results are highly valuable inputs for farmers when determining which crops would be most suitable given local conditions and their yields thus improving agricultural productivity through advanced technologies efforts with ease.

## II. LITERATURE SURVEY

### WHAT ARE THE ALGORITHMS?

### (I)ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Networks (ANNs) are a type of machine learning model that are inspired by the structure and function of the human brain. They consist of layers of interconnected “neurons” that process and transmit information. ANNs are computational models inspired by an animal’s central nervous systems. It is capable of machine learning as well as pattern recognition. In general, the combination of ANN and RNNs can be used for time series forecasting problems. ANN can be used to extract features from the time series data.

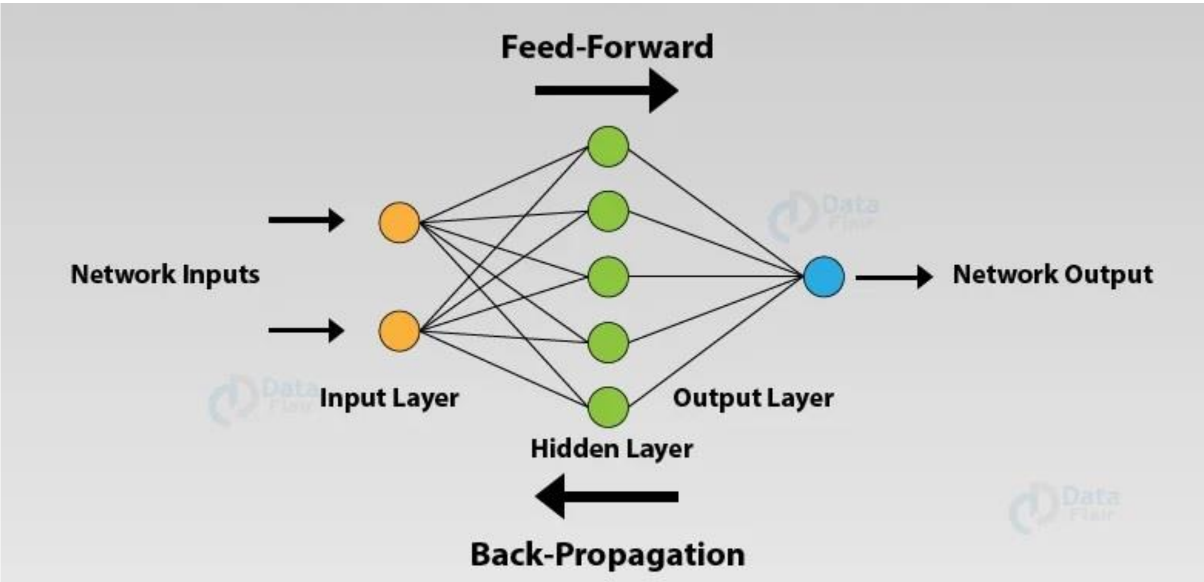


**Fig a. Working of Artificial Neural Network**

  

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**(ii) Recurrent Neural Network (RNN):** RNNs (Recurrent Neural Network) is a type of artificial neural network which uses sequential data or time series data can be used to predict the future values.

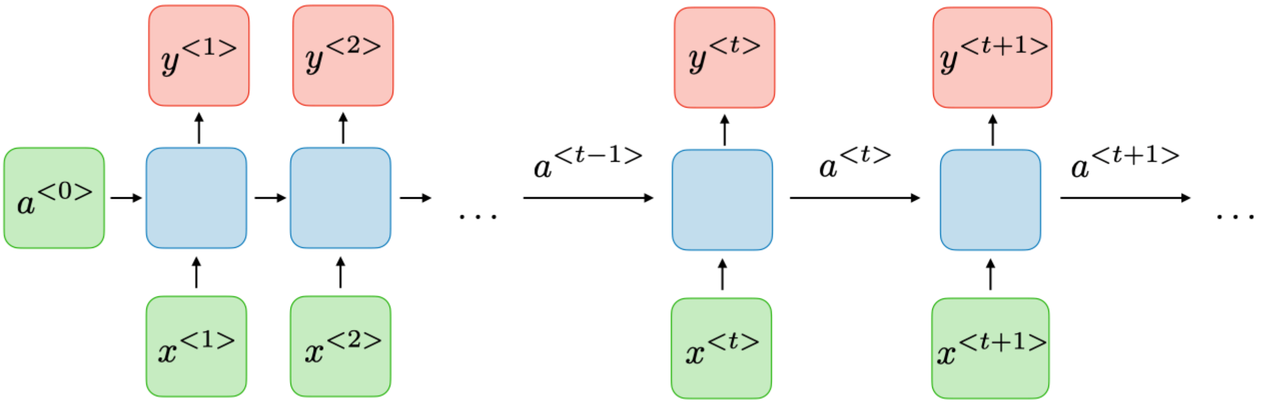


**Fig b. Working of Recurrent Neural Network**

**(iii) CONVOLUTIONAL NEURAL NETWORK (CNN)**

A Convolutional Neural Network (CNN) is a type of artificial neural network specifically designed for analysing visual data. It is widely used in image and video recognition tasks, as well as in other applications such as natural language processing and audio analysis.

CNNs are inspired by the organization and functioning of the visual cortex in animals, particularly the receptive fields of neurons. They consist of multiple layers of interconnected nodes, with each layer performing different operations on the input data. The core operation in a CNN is the convolutional layer, where filters or kernels are applied to the input image to extract various features. These filters slide over the input, performing element-wise multiplication and summing the results to produce feature maps. The idea behind using convolution is to capture local spatial relationships between pixels. Typically, a CNN architecture consists of multiple convolutional layers, followed by pooling layers that reduce the spatial dimensions, and then fully connected layers that perform classification or regression. Activation functions like ReLU (Rectified Linear Unit) are commonly used to introduce non-linearity.

During training, CNNs learn to adjust the weights of their filters through a process called backpropagation. The model is presented with labelled training data, and it updates the weights based on the error between its predicted output and the true output. This iterative process allows the network to learn and improve its ability to recognize patterns and features in the data. CNNs have been remarkably successful in various computer vision tasks, such as object detection, image classification, semantic segmentation, and facial recognition. Their ability to automatically learn hierarchical representations from raw data has revolutionized the field of deep learning and has significantly advanced the state-of-the-art in visual understanding.

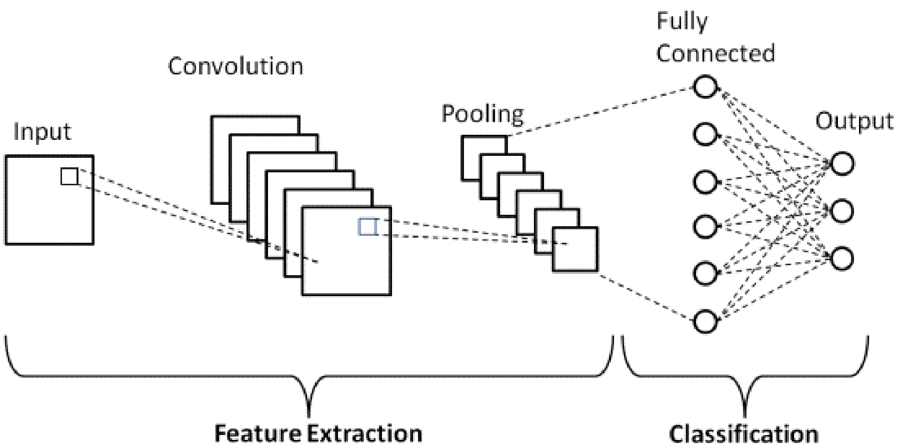


**Fig c. Working of Convolutional Neural Network**

 

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## III. HOW IT WORKS?

Indian farmers face so many problems that they will end up suffering losses. It is a social problem that can be solved or reduced by using technology. We're trying to build machine learning models to advise farmers on how to grow better crops on specific soils and to know how much their fields will end up yielding. ML technology can solve this problem, so we thought about working on this project.

At present deep learning, computer vision, image processing, robotics and IoT technologies are very supportive to farmers. AI based drone technology is very helpful for farming because it makes it easier to monitor, scan and analyse the crops by providing high quality yield. This technology is useful to identify the progress of the crops. There is no limit to describe the applications of deep learning in Agriculture even some of the applications of Deep Learning in agriculture are given below.

1. Data Collection: Collect data related to crop production, including historical yield data, weather data, soil data, crop management data, and any other relevant information that may impact crop yield or quality.
2. Data Pre-processing: Clean, pre-process, and format the collected data to make it suitable for use by the machine learning algorithms. This includes tasks such as data cleaning, data normalization, and data augmentation.
3. Feature selection: Identify the relevant features or variables that can help predict crop yield. Feature selection can be done using techniques such as correlation analysis, principal component analysis, and mutual information analysis.
4. Split Data: Split the pre-processed data into training and testing sets. The training set is used to train the machine learning model, while the testing set is used to evaluate the performance of the model.
5. Model Selection: After selecting the features, select the appropriate machine learning model. This will depend on the type of data and the problem being solved. Popular models for crop yield prediction include random forest, support vector machines, artificial neural networks, and K-nearest neighbours.
6. Model Training: Train the selected machine learning model on the pre-processed data. This involves splitting the data into training and validation sets and then using the training set to train the model.
7. Model Evaluation: Once the model is trained, evaluate it using the validation set. This involves testing the model's accuracy and performance and fine-tuning its parameters to improve its performance.
8. Deploy the Model: Deploy the machine learning model in a production environment where it can be used to make crop predictions on new data. This could be in the form of a web or mobile application that farmers can use to get recommendations on which crops to plant and when to plant them.
9. Prediction: Use the trained and validated model to make predictions on new data. For example, given weather and soil data for a particular season, predict the crop yield for that season.
10. Monitor and Improve: Continuously monitor the machine learning model's performance and gather feedback from farmers and other users. Use this feedback to improve the model and make it more accurate over time.

Overall, this architecture provides a general overview of the steps involved in using machine learning for crop prediction. The specific details and requirements of each step may vary depending on the specific problem at hand.
Note: This architecture is a general overview of the process and may vary based on the specific requirements and constraints of the crop prediction system.

## IV. WORKING PROCEDURE.

*Artificial Neural Networks (ANNs):*
ANNs are versatile models that can be employed for crop yield prediction by considering various input features such as weather data, soil characteristics, crop management practices, and historical yield data. The ANN architecture consists of input, hidden, and output layers of interconnected nodes (neurons). The key steps involved are as follows:

Data Preparation: Collect relevant historical data, including weather information, soil composition, fertilizer usage, pest control measures, etc.

Feature Selection/Extraction: Identify the most significant input features that can impact crop yield.
Training: Train the ANN model using the historical dataset, where inputs are the selected features and the output is the corresponding crop yield.

Testing and Validation: Assess the model's performance by evaluating its predictions against a separate validation dataset.
Prediction: Once trained, the model can predict crop yield for new input data.

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*Convolutional Neural Networks (CNNs):*
CNNs are predominantly used for image-based tasks, but they can also be applied to crop yield prediction by leveraging satellite imagery or aerial photographs of crops. The steps involved are as follows:

Data Collection: Acquire satellite imagery or aerial photographs covering the crop area of interest.

Image Pre-processing: Pre-process the images to enhance relevant features, normalize values, and remove noise.

Training: Annotate the images with crop yield information (e.g., yield per field or pixel) and train the CNN using a suitable architecture.

Testing and Validation: Evaluate the model's performance by comparing predicted yield values against ground-truth measurements or additional data sources.

Both ANN and CNN models require careful consideration of feature selection, data quality, model architecture, and appropriate training and validation procedures to achieve accurate crop yield predictions. The choice between ANN and CNN would depend on the nature of available data and the specific requirements of the crop yield prediction task.

Prediction: Apply the trained CNN to new images to estimate crop yield for the corresponding areas.

The detailed algorithm for ANN plus CNN is as follows:

1. Collect the data for crop yield prediction.
2. Pre-process the data by removing the missing values and outliers.
3. Split the data into training and testing sets.
4. Train the ANN model on the training set.
5. Train the CNN model on the training set.
6. Combine the output of ANN and CNN models.
7. Train the combined model on the training set.
8. Test the combined model on the testing set.
9. Evaluate the performance of the combined model using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$).

Hybrid ANN-CNN algorithms combine artificial neural networks (ANN) and convolutional neural networks (CNN) and can be used to predict crop yields. This algorithm leverages ANN and CNN capabilities to analyze and predict crop yield based on various input characteristics such as weather data, soil quality, crop type, and historical yield data.

Obtaining crop yield prediction results using the hybrid ANN-CNN algorithm typically involves the following steps:

Data collection:
Collect the data required for the predictive model. This may include historical crop yield data, weather data, soil properties and other relevant characteristics.

Data preprocessing:
Clean up the collected data and preprocess it for analysis. This step may include data normalization, feature scaling, missing value handling, splitting the dataset into training and testing sets, and so on.

ANN training:
Train an artificial neural network (ANN) using the preprocessed dataset. ANN learns patterns and relationships between input traits and crop yields. Based on the complexity of the problem, we can choose the architecture of the ANN, including the number of layers and neurons.

CNN training:
Train a convolutional neural network (CNN) using the preprocessed dataset. CNNs are specifically designed to process spatial data such as satellite imagery and grid-based data. If you have such data, you can use CNNs to extract traits that are meaningful for crop yield prediction.

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Hybrid model integration:
Combine pre-trained ANN and CNN models to create hybrid ANN-CNN algorithms. This integration can be done by feeding the output of the CNN as input to an ANN for further analysis and prediction.

Model evaluation:
Evaluate the performance of the hybrid ANN-CNN algorithm using the test dataset. This evaluation can include metrics such as mean squared error (MSE), mean squared error (RMSE), and coefficient of determination (R-squared) to assess the accuracy and reliability of predictions.

Crop Yield Forecast:
Once the model has been evaluated and found satisfactory, it can be used to predict crop yields by providing new input data such as current weather conditions, soil quality and other relevant characteristics can.

It is important to note that implementing and fine-tuning hybrid ANN-CNN algorithms requires expertise in machine learning and deep learning. Furthermore, model success depends on the quality and representativeness of the input data.

## V. RESULT

**Current system:**

The systems currently in use have many limitations. Until now, few forecasts yielded more than 30% yield. In this supply, when the crop is identified and the area is calculated, the area is displayed instead of the actual yield. Yields depend on a number of variables, including: B. Plant Health and Weather. Critical analysis, investigation of research gaps, recommendations and future directions are lacking. Current methods that avoid other traits, such as soil nutrients, focus on machine learning algorithms for predicting crop production-based parameters.

Just for meteorology most systems do not provide a meaningful assessment of current machine learning techniques. Furthermore, traits that influence crop yield prediction models have not been studied.

Drawbacks: No exhaustive processing of the data has been performed. Mathematical analysis are omitted. No detailed graphic check, about weather and favourable predictions of crop etc.

**Proposed system:**

It includes many factors such as meteorological factors, soil parameters, terrain data, etc. We work together to build crop yield and recommendation systems. Analyse the data using Plotly, Matplotlib, and Seaborn to gain valuable insights into your data. Correlation is used to determine the probability that a feature will be selected. Remove unnecessary data by identifying outliers using z-scores to minimize overfitting.

It provides highly accurate crop yield prediction models. Providing farmers with recommendations for growing crops

It depends on soil and weather conditions. • Development of plant recommendation system including data analysis of soil factors including temperature, humidity, pressure, N, P, K; Soil information should be included in the system

It is advantageous as it influences crop selection. State, county, year, season, and crop name are considered to predict yield. Area. Temperature, wind speed, air pressure, and humidity. It recommends ideal cultivation based on nitrogen, phosphorus and potassium availability, temperature, humidity, pH and rainfall.

## VI. CONCLUSION

The result of implementing ANN and CNN algorithms for crop yield prediction would depend on the specific dataset and problem at hand. In general, the combination of ANN and CNNs can be used for time series forecasting problems. ANN can be used to extract features from the time series data and CNNs can be used to predict the exact crop yield values.

Time series forecasting is the process of analysing time series data using statistics and modelling to make predictions and inform strategic decision-making. It involves building models through historical analysis and using them to make observations and drive future strategic decision-making

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