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CONSTRUCTION OF NOVEL NEURAL NETWORK MODEL BASED ON NEUROEVOLUTIONARY ALGORITHM FOR IMPROVING THE PERFORMANCE OF CROP YIELD PREDICTION

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Abstract

The development of machine learning combined with high speed computing power has opened up several multidisciplinary opportunities. Here, we provide a cutting-edge machine learning technique for forecasting agricultural production. The performance enhancement in agricultural yield prediction was proven by the classification approach utilising machine learning algorithm. It depends on the local soil, water irrigations, and meteorological variables that are related to data on climate change. Here, we've provided an example of how to use an ANN-based neuroevolution model to forecast wheat crop production. From June through September, crop yield projections are taken into account. The yields are generated based on climate and fertilizer usage statistics. The capacity to forecast how a season will evolve based on weather information has significantly improved. As a consequence, the model's results help with decision-making before planting a wheat crop. The findings are more helpful for making decisions, planning wheat planting, and performing other agricultural duties at various stages of the wheat crop's development. The same model may be utilised to predict a variety of agricultural data, such as disease and weather predictions.

In this work, a neural evolution system for forecasting different plant illnesses was created. The performance increase in plant disease diagnosis may be proven using the algorithms of machine learning that support several categorization strategies. Disease prediction is based on local soil conditions and meteorological variables that are related to data on climate change. Here, we've shown how to use an ANN-based neuroevolution model to forecast a variety of plant illnesses. Different causes and the sort of illness that may harm various plants at various times of the year are anticipated. As a result, the results of the suggested model help with decision-making and preventative measures for plant diseases. The results may be used to make decisions early on about plant disease prevention as well as numerous farm operations at different stages. The technique used for forecasting different agricultural data, including crop yield and weather prediction, is also utilised here.

The paper's primary goal is to use a cutting-edge neuroevolutionary algorithm to analyse agricultural yields more accurately. One of the biggest issues of the twenty-first century for sustainable and nutrition security for a population increase is climate, which is putting the world's food security in jeopardy now. Water scarcities, exorbitant expenses brought on by supply and demand, and unpredictability of the weather are among the present problems. Farmers were exhorted to enhance their farming practices. The main causes in agriculture are the shortage of crops that can be grown using conventional agricultural methods, the uncertainty surrounding climate change, the absence of irrigation infrastructure, the paucity of land, and the scarcity of crops. To anticipate crops, many machine learning methods like perception, divisions, regress, and aggregation are applied. Some of the mathematical techniques employed to carry out the prediction include artificial network, vectors support networks, linear and linguistic matrices, decisions trees, and Bayesian intelligence. It is clear that choosing the appropriate methods for sample design is a difficult task for academics. The ability of machine learning systems to forecast agricultural yields has been investigated. The techniques created to provide predictions using machine learning. The outcome demonstrates that, when compared to other approaches, the neuroevolutionary algorithm is more successful. We modified this method to learn graphical images of plant diseases and demonstrate that going to discriminate infected areas of a plant can be satisfactorily located and

emphasised for disease identification. This work was inspired by latest projects on multi-organ recognition and classification that has demonstrated the capacity of an interest Rnn Model (RNN) to locate applicable regions of various plants without even any prior human annotation.

1. INTRODUCTION

The term "Neuroevolution" refers to the concept of applying genetic algorithms that are evolving. Neuroevolution algorithms are mostly employed in network topology analysis, and because they can find the best answer, they may be applied to the prediction of crop production. The majority of agriculture in India is devoted to growing wheat, which is significant to the world economy. Pressure to boost agricultural productivity is growing due to population growth. New scientific fields that can significantly increase agricultural output have emerged as a result of technological growth in agriculture and farming. While the machine learning algorithm is supported by a scientific method that gives computers the capacity to learn on their own without being precisely programmed [2]. Based on their nutritional content and capacity for climate change adaptation, the wheat types are chosen using certain genes. Learning-based algorithms are useful in agriculture because they analyze crop yields in relation to varied climatic conditions, soil types, and fertilizer application. This analysis can assist in the development of a prediction that can be used to help with crop planting.

The illness that damages the plants at the harvest time is difficult to distinguish in agriculture since it is a localised industry. The goal of this study is to apply a machine learning algorithm to identify damaged plants by looking at their morphology. Diseases or pests can wreak havoc on the food industry, resulting in decreased food output. To lessen the stress of the post-harvesting process, many technological advances have been created. While several methods, including polymerase chains reaction, thermography, chromatography, etc., are used to diagnose infections, hazardous pathogens and inadequate disease control are the main causes of decreased food production. . Therefore, the focus of this work is on machine learning algorithms for disease prediction in plants. Crop protection is aided by essential technology that can automatically identify plant diseases at an early stage. As a result, we are putting mechanisms in place for spotting illnesses in different plants early on. Hyperspectral data is used to examine both healthy leaves and stems that have been infected with beticola, betae generating leaf blight, beet rust, and downy mildew. Various algorithms are used to identify healthy and vaccinated plants before they become infected with a particular disease.

The finding that the impacts of global warming have a substantial influence in crop output is in line with the fact that there is ambiguity regarding climate change and rain in India. Due to the unpredictable weather, Indian farmers have recently had difficulty selecting the best crop to grow. Artificial intelligence can help with crop output forecasting in different parts of India under diverse climatic circumstances, solving this challenge in the agricultural industry. Various climatic or temperate conditions are suitable for growing a variety of crops. Examine the effects of the weather on crop growth and the effects of the weather on crop growth. In order to compare the variations in yield over time, a study of values in India from 2000 and 2018 would be conducted. These yields will be included into a database of crop production in India's producing areas. The weather was warm at this time. Through the blossoming season, there is a noticeable rise in dry weather in India, which suggests a shift in the way rain is distributed. In South India, output of rice, wheat, and peanuts has changed without any discernible pattern since the 1960s (30%). The quantity of cotton and corn produced annually in the rain. According to a research, due to changes in rainfall patterns, changes in climate has a particularly significant effect on rice cultivation in southern India. Indian food, water, and electricity shortages as well as public health have all been significantly impacted by climate change. Scientific study is increasingly focused on the global warming effects and potential adaptation strategies. Numerous parameters are used to estimate crop production and soil moisture. Learn about agriculture items to help in the construction of a fresh drinking water home. Higher agricultural yields from more drainage in high-yield farming regions lead to more ecological harm. Shorter agricultural growth periods than in the future as a result of climate change's effects on water balancing, soil degradation, and resource distribution might threaten food quality and the environment. Certain regional climates emerge while others deteriorate as a result of changes in latitude and irrigation practices in the area.

Agricultural production are more responsive to rains than to temperate conditions, according to main product models, and crop yields increase as rainfall increases. Soils with deeper moisture content would be able to combat drought more successfully when water supply decreases. Future temperature increases and rainfall variations may negatively affect agricultural yield. Crop yields improve with greater irrigation area. But there is a chance that the ecology and food quality might be harmed.

1.1.PROBLEM DEFINITION

- Crop protection is made possible by essential technology that can automatically identify plant diseases at an early stage.
- Soils with deep moisture would be able to combat drought more successfully when water supply decreases. To stop water decreases, we thus need improved methods.

1.2.RESEARCH MOTIVATION

- The kind of soil in that location was taken into consideration as one of the features since soil is a natural resource that significantly influences crop productivity. The soil type is in charge of the intricate systems and complex processes.
- Depending on the kind of soil, it may also take into account soil moisture, temperature, and evaporation processes in order to identify the importance of ecosystems and their impact on agriculture.

- Water is another natural resource that significantly affects agricultural cultivation. Since irrigation method affects agricultural output, we have added irrigation method as one of the parameters for yield prediction. Agriculture's use of water affects the hydrological, climatological, and agronomic balances.
- To create and run the training model using the relevant input data. As a result, the model may use machine learning techniques to extract crop production from the data while also learning the characteristics.

1.3.OBJECTIVE

- To demonstrate a method for using an ANN-based neuroevolution model to estimate wheat crop yield.
- To demonstrate a method for using an ANN-based neuroevolution model to the prediction of various plant diseases.
- To compare the neural evolution method with other common algorithms, such as KNN and SVM, for predicting crop yield.
- Motivated by previous research on multi-organ plant recognition that demonstrated a media exposure Recurrent Neural Network (RNNcapacity)'s to find important areas of plant structures without even any prior human annotation.

2. LITERATURE SURVEY

In 1997, Harvey et al. proposed a neural system controller that paved the way for the creation of mobile robots, vehicles, and rockets. The control structure for PC development is improved by this framework. According to Lucas (2005), neuroevolution may be utilised to design complicated procedures and even continually alter them. A similar concept is suggested to be applied in constructing counterfeit detection systems.

In order to estimate maize output in the US Midwest, Acharya N et al. propose the use of nonparametric neural networks. The author shows that nonparametric neural networks outperform fully-nonparametric neural networks as well as both statistical techniques. Based on situations where climate models indicate significant negative effects on maize yield, although statistical approaches indicate smaller consequences. Therefore, in the driest areas, his strategy is less depressing.

Neuroevolution is a method for creating artificial intelligence that was developed with biological inspiration. There are several unresolved issues in building efficient and scalable evolutionary algorithms that produce highly intelligent systems. Scaling the neuroevolution algorithms causes cognitive processes including multidimensional actions, communication, and lifelong learning to develop. Because of practical methods to evolution like neural networks in biology and the development of intelligence itself, autonomous robotic controllers and video gaming consoles have all been produced. Better neuroevolution methods may result from overcoming the hurdles.

Back propagation is a popular approach used to train neural networks because it makes it possible to calculate the gradient of the loss function more quickly. This approach has shown excellent results for supervised learning as well as notable reinforcement learning outcomes. For a comparison to frequently utilised recent deep network (DNN) research, the majority of successful applications used the creation of small neural networks utilising contemporary standards.

A GRNN (Generalized Regression Neural Network) method is suggested by YounesChtioui et al. for forecasting leaf wetness. One of the key elements that contributes to plant disease is leaf wetness. As a result, the writer of this study examines the many climatic factors that can have an impact on plant diseases and leaf wetness. Soil Water, etc., and then obtained the training and testing set results with actual prediction error ranges of 0.1414 and 0.1300. Additionally, the prediction errors for the testing and training phases, respectively, were 0.0491 and 0.0894, demonstrating that the GRNN approach is more accurate than MLR.

A technique of wheat pest prediction assessment is suggested in a publication by Jessica Rutkoski et al. Regression Model, Multiple Regression, Bayes Logistic regression, Procreating Cylindrical Hilbert Space Regression, and Randomized Forest Recurrence are among the evaluation models; as a result, the model utilising biological markers and Sequencing Technologies Loci has the best precision.

In a study employing MLR, D. C. Hooker et al. identified three times and circumstances when catalyzed oxidation occurs. From 1996 to 2000, their research gathered pertinent data from 399 farms in Ontario, a province in southern Canada, to forecast the incidence of deoxynvalerate. In an experiment, daily wetness, temperatures, and moisture values for every hour were gathered as meteorological variables. It was shown that deoxynivalenol occurrence is correlated with wheat growth, rainfall intensity, and temperature. Additionally, it has been demonstrated that ambient moisture has no bearing on the emergence of plant diseases; as a consequence, the accuracy value was attained at roughly 89% with a cutoff value of 2 micrograms.

3. AN EMPIRICAL STUDY OF NEUROEVOLUTIONAL MACHINE LEARNING- BASED ALGORITHM FOR PROJECTING CROP YIELD

3.1.NEUROEVOLUTION

The development of natural organic systems was used to construct the Artificial Neural Networks approach known as the neuroevolution algorithm. Neuroevolutionary strategies are more effective and suitable for problem-solving, and they are used in the creation of evolutionary robots. Neuroevolution may be viewed as a method of examining how knowledge evolved in nature and as a tool for creating artificial brain systems that perform necessary functions. Neuroevolution employs peculiar tactics that result in erratic environments and fortified learning. Few demonstrable applications that support learning are integrated into these fields; the most obvious example is the flexible, unpredictable control of physical objects.

3.2.1 Yield Prediction Elements

As a result, mapping and forecasting crop output in relation to demand is known as yield prediction. Modern methods have advanced past basic predictions made on the basis of historical information, but later attempting to incorporate techniques for computer vision it gives specific information about data conversion of crops, and climate which can assist the vast majority of farm owners and population to improve crop yield. By equally spraying pesticides throughout the cropping area, disease diagnosis in plants aids in pest management [19]. This method incurs substantial costs since it calls for large quantities of insecticides. In order to manage agricultural operations with a general level of accuracy, grow-chemicals are delivered as inputs and targeted based on the time, location, and impacted plants [2]. Weeds have an impact on crop output similar to disease The main problem with eradicating weeds is that they are more challenging to find and differentiate from crops. Without harming the crops, computer vision and machine learning algorithms can increase the precision of weed detection and differentiation. Machine learning algorithms can make precise predictions to maximize the most economical animal production methods, much like crop management.

3.2 CONSIDERED FACTORS FOR MODEL CONSTRUCTION

With the help of geographic and meteorological information, this study aims to forecast wheat yields. Statistics on the place, timing, and wind speed are included in the dataset. A feature, such as the start of the month, is used to compute the season. To predict wheat yields, several parameters are employed.

The model is created in a way that it can estimate which month will provide the highest production of wheat over a particular period of time. then afterwards it is projected which place would provide a higher yield depending on the wheat production in each area. Missing and NULL/NaN values are removed as part of the preprocessing of the data collection [1]. Here, weather-related information varies with time and place. The average value derived from previous and following days' recordings at the targeted area is used to replace the missing value. For the trials, characteristics like place (latitude and longitude), season (weather, temperature, humidity, and month), are taken into account. The following final characteristics were incorporated into the modelling:

Feature	Description
location	Latitude and longitude of the place in degrees.
humidity	The normal humidity of the region, expressed in g/m3,
rainfall	Average rainfall for the area for the given time period, expressed in mm.
mintemp	Minimum temperatures during the course of 60 days or during months with

	minimum temperatures.
maxtemp	Maximum temperature during a 60-day period or during the coldest months.
wind speed	a location's computed average wind speed
mean temp	The typical spread of daily temperature fluctuations
yield	By season's end, any crop's maximum yield value

3.4.Algorithm

Any mutation strategy, such as adding or removing values from altered weights, can be used in neuroevolution.

Step 1: Values for the data input are first established.
Step 2: Special Features are computed (Location, Season)
Step 3: neural network construction (neuroevolution)
Step 4: The mutation strategy for neural networks is used.
Step 5: The biases are multiplied by the random values that are closest to 1.
Step 6: Substitute the new value for the prior biases.
Step 7: Adjust certain values to account for bias.
Step 8: includes substituting several weight values for particular weighting components.
Step 9: Inform the Model.
Step 10: To assess the Performance, use the test set.
The effects of several mutation strategies are compared [17]. As a consequence, fig 3 shows the best outcome attained.

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3.5. RESULT AND DISCUSSION

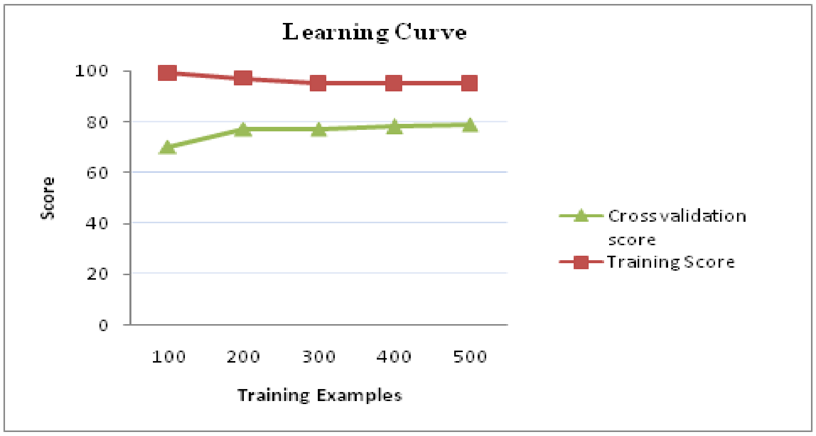


Figure 3.1: Training Scores and Cross Validation Learning Curve

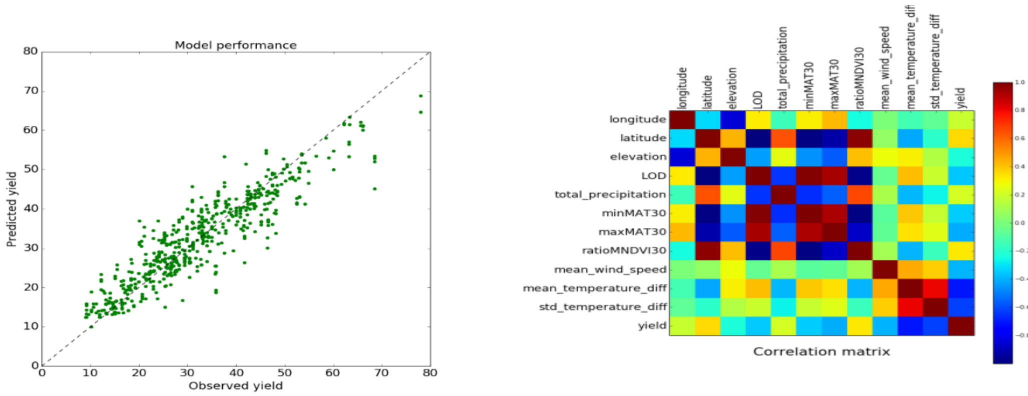


Fig. 3.2: Wheat Yield Model Prediction

Whereas the supplied testing dataset has an RMSE of 24%. While the proposed system appears to be consistent under prediction when higher yields are seen, the prediction for lower yields appears to be well-balanced.

4. AN EMPIRICAL STUDY OF MACHINE LEARNING METHODS FOR PREDICTION OF PLANT DISEASE

4.1.DATA SET

Plant Diseases and Their Potential Causes

Black splotches that develop leaf yellowing surrounding them are the symptoms of the disease known as "black spot," which affects bushes like roses. Black spot commonly develops on freshly developing leaf tissue in damp, humid circumstances and is typically wind- and rain-spattered. Plant "dust" that is brown or speckled and may include silver spore on the dying or dead tissue is known as botrytis blight. Except for the roots, it can harm anything part of the plant. The fungus that causes rust spreads when spores from it fall from the sky and touch down on plants. Rust does not really kill plants, although it can hasten their demise. fluffy mildew Powdery mildew is a term used to describe a variety of fungal strains. Because this illness depletes the plant of vital nutrients, leaves may turn yellow, become stunted, or drop off too soon. Both healthy leaves and those with the diseases spot, rhizome blight, and powdery mildew—are harvested for the experiment.

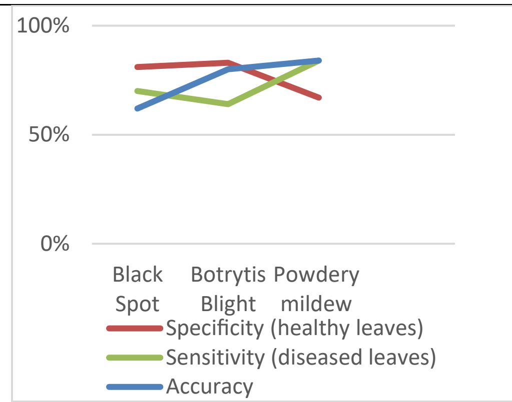
Step 1: The values of the data input are established first.
Step 2: Specific Features are computed (Location, Season)
Step 3: constructing a neural net (neuroevolution)
Step 4: The neural network's mutation approach is implemented.
Step 5: The biases are multiplied by the random values that are closest to 1.
Step 6: Substitute the new value for the prior biases.
Step 7: Adjust certain values to account for bias.
Step 8: includes swapping out distinct weight values for other weight values.
Step 9: Teach the Model
Step 10: Utilize the exam set to assess performance.

4.2. Results:

Many data mining methods were effectively employed in earlier research projects to distinguish between healthy and sick leaves. In this work, we applied the continuous phase technique to anticipate three distinct illnesses, including black spot, rhizome blight, and powdery mildew. The findings are shown in Table 1 below.

Table 4.1: Sensitivity, accuracy, and specificity for different diseases

Classification [%]			
Leaf disease	Accuracy	Specificity (healthy leaves)	Sensitivity (diseased leaves)
Black Spot	73 %	81 %	71%
Botrytis Blight	80%	83%	64%
Powdery mildew	85 %	67 %	84%



5. USING A NEURO EVOLUTIONARY ALGORITHM TO ANALYZE THE CLIMATE CHANGE IMPACT ON IRRIGATED CROPS' CROP YIELDS AND THEIR WATER NEEDS IN INDIA.

5.1.OVERVIEW

The data set was gathered from Kaggle and includes statistics on agricultural productivity. Data about production costs in agriculture. Data on cultivation and production are from Indiastst and Data.gov.in, respectively**.**

5.2.PROPOSED NEUROEVOLUTION ALGORITHM

Numerous mutation strategies can be used in neuroevolution.

Step1: locating and gathering pertinent input data

Step 2: Take into account the features attributes that are necessary for computation, such as Place, Season, etc.

Step 3: Building a neural network based on relevance feedback (neuroevolution).

Step 4: Use mutation to identify the neural network that is most suitable.

Step 5: Use random values, taking the nearest into account when multiplying by a bias value.

Step 6: Put the new bias value in place of the old one.

Step 7: Weights can be changed to increase bias levels.

Step 8: Creating the Model

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Step 9: Utilize the exam set to assess performance..

5.3.RESULTS AND DISCUSSION

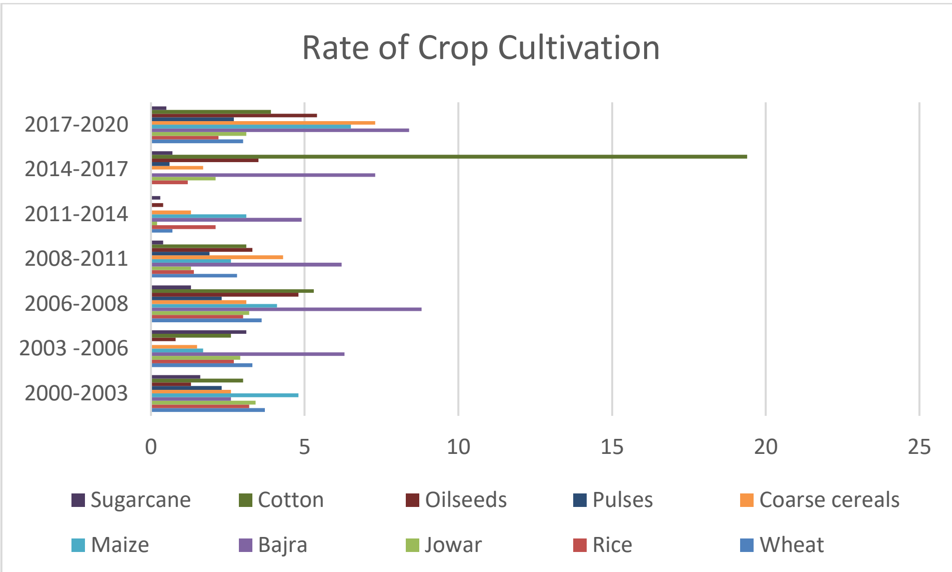
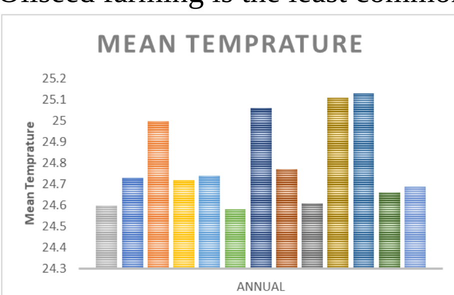


Figure 5.1: Rate of crop cultivation in India

The data of different crops that were grown in different regions from 2000 to 2019 are shown in Fig 5.1. Sugarcane, cotton, oilseeds, pulses, coarse cereal, maize, Bajra, Jowar, rice, and wheat are among the several types of crops. Pulses were more widely grown from 2014 to 2017 than any other crop, as shown in Fig. 3. Oilseed farming is the least common.



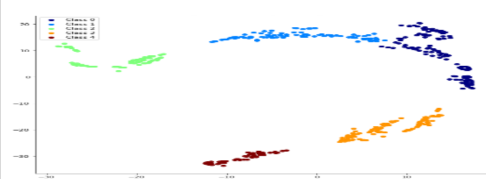


Figure 5.2 shows the average temperature from 2006 to 2018 and the crops that produced the most in each state.

The mean annual temperature of different regions is shown in Fig. 2 for the years from 2006 to 2018. The temperatures is taken into consideration while analyzing the maximum crop production with relation to season and temperature since climatic conditions have a significant impact on agricultural output. Whenever the mean temperature is high, it is found that only sugar yield are significant all throughout years 2015 and 2016, but wheat, oilseed, and paddy crop yields are all much lower. Therefore, it demonstrates that temperature conditions have a significant impact on yields.

6. CONSTRUCTION OF NOVEL NEURAL NETWORK BASED ON NEUROEVOLUTIONARY ALGORITHM FOR IMPROVING THE PERFORMANCE OF CROP YIELD PREDICTION

6.1.METHODS

Two steps make up the suggested methodology:

1) Prediction of seasonal weather and
2) Selecting an appropriate crop. It employs recurrent neural networks (RNN) to anticipate seasonal weather.

Then, using a random forests classification algorithm, appropriate crops are categorised. Deep learning is made possible for farm-scale agricultural production prediction by a new dataset containing real-world per-farm samples that was developed by fusing various data sources. To maximize prediction accuracy and test various hypotheses, many models are presented. A convolutionary, recurring, and hybrid model is the one that is the most accurate. To forecast agricultural yields, it integrates multispectral satellite photos and meteorological information. To the best of our knowledge, the model is a first of its sort for predicting farm-scale crop yields. Additionally, the aggregated farm-scale projections to a commune size are shown. The suggested approach produced results that were equivalent to the most recent, cutting-edge crop production estimates.

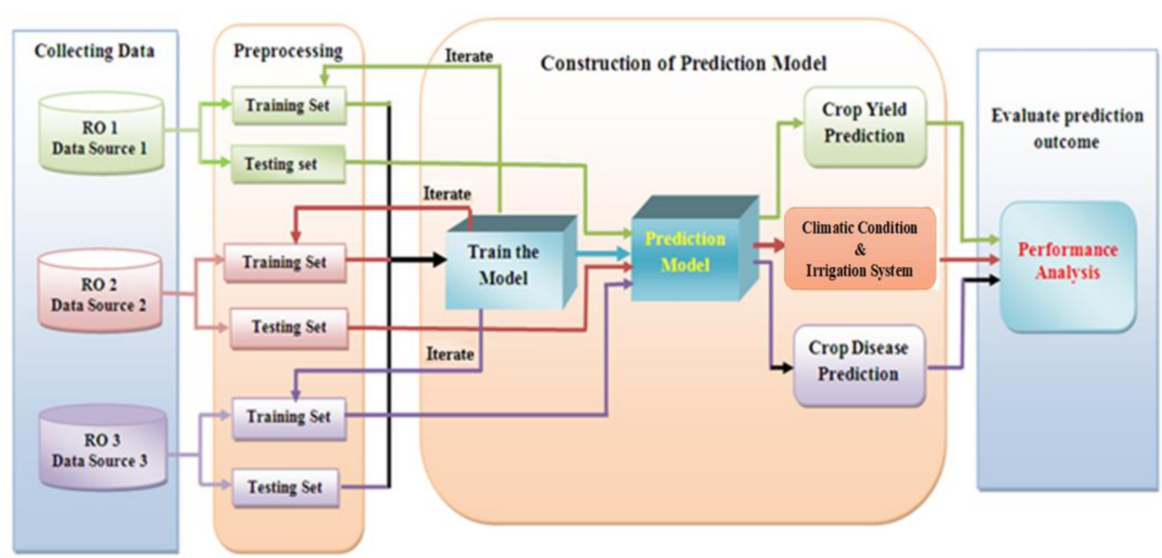


Figure 6.1. General layout

6.2.Algorithm for IRNN(Integrated Recurrent Neural Network)

- Step 1: Construct the model of the system architecture for a neural network.
- Step 2 is to train the data model.

Step 2.1 is to examine the loss on the training crop data set.
Step 2.1.1: Continue the filtering procedure
Step 2.1.2: Determine the mistake in empty cell terms.
Step 2.2: Review the mistakes prior to data validation.
Step 2.2.1: Send the verified data to the feature extraction step
Step 2.2.2: Identify the mistake
Step 2.3: Begin the training itself
Step 2.3.1: Send the training batch of data for prediction
Step 2.3.2: Use back propagation to determine the accuracy of the prediction error
Step 2.3.3: Revise the weighting for the chosen fields

• Step 3: Inputs – even though you may just have one providing job, you must send three-number sequences as your input since the recurrent layer requires it, i.e. [x0, x1, x2],..., [x n-2, x n-1, x n].
• Step 4: Training Model – In a normal feed-forward neural net, the hidden node will contain weight and bias as its two parameters. In contrast, the weight again for input, the weighting for the hidden layer, and the bias parameters for a diagram (fig for the training phase must all be optimised.

• Step 5: Training feature model Extraction: A staple food neural network is developed using a back propagation neural technique. As a result of the folding in time and train the values of the field that are taken into account for prediction, a slightly altered version called back propagation is used while training a neural network model to find the mistake.

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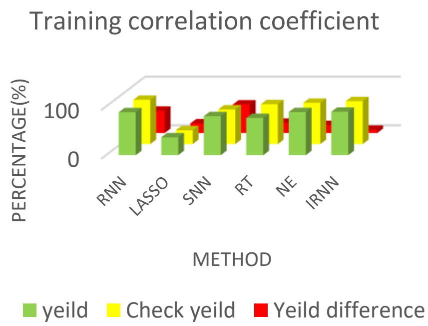
6.3.RESULTS

Table6.1. A comparison of correlations

Model	Response variable	training data set	Timing correlation coefficient(%)	validation of data set	validation correlation coefficient(%)
RNN	yield	10.55	88.3	12.79	81.91
	check yield	8.21	91.00	11.38	85.46
	yield difference	11.79	45.87	12.40	29.28
Lasso	yield	20.28	36.68	21.40	27.56
	check yield	18.85	28.49	19.29	23.00
	yield difference	15.32	19.78	13.11	6.84
SNN	yield	12.96	80.21	18.04	60.11
	check yield	10.24	71.18	15.18	60.48
	yield difference	9.92	58.74	15.19	11.39
RT	yield	14.31	76.5	15.03	73.8
	check yield	14.55	82.00	14.87	69.95
	yield difference	17.62	21.12	15.92	5.1



Training correlation coefficient, Figure 6.3

Table 6.2. Comparison of accuracy and MAPE

Method	Accuracy (%)	MAPE (%)
RNN	94.64	12
LASO	92.13	15
SNN	91.89	13
RT	95.65	5.4
NE	97.4	3.8
IRNN	98.9	1.2

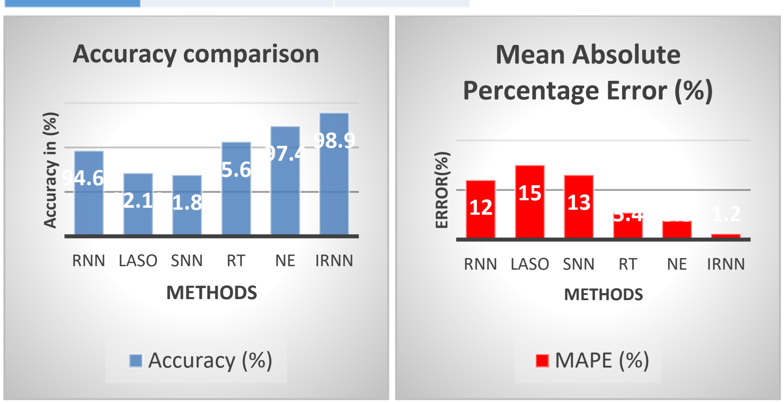


Figure 6.4. Comparison of accuracy and mean absolute error percentage

7. CONCLUSION

A neuroevolution approach is suggested in this work for forecasting wheat production while taking into account a variety of factors, including location, quantity of rains, temperature, wind speed, and humidity level [18]. Taking into account the monthly statement that provides a total value for the given time period However, as the wheat yield prediction model needs daily weather information, a disaggregation approach is utilised to create such daily data set. To evaluate the crop's productivity at different stages of the several seasons in connection to the anticipated amount of rain and temperature changes, wheat yield has been simulated. The examination of the season and monthly data for wheat production showed excellent yield forecast accuracy. Additionally, improvements in the capacity to forecast wheat productivity have been shown before the particular season. This is due to the fact that, after the incorporation of experiencing weather data from succeeding months, yield forecast uncertainty decreases as crop encounters weather that is more frequently seen for the projected type. In the current work, the suggested model was trained using data spanning five years. The study's findings will be helpful in coastal Indian regions when choosing the best time to plant wheat. It also extends to other significant crops grown there, such as rice, corn, sugarcane, etc., to assess how well they perform under anticipated weather conditions. This aids in choosing the right crop to cultivate during the monsoon season.

Plant diseases have been simulated in order to assess the potential for disease at various phases of the relevant season. The seasonal and monthly data collected are evaluated with illnesses caused and substantial accuracy in plant disease prediction is shown. Additionally, improvements in the capacity to forecast wheat productivity have been shown before the particular season. This is because, following the incorporation of observed weather data in the updates of successive months, uncertainty in yield prediction diminishes, as crop experiences the weather conditions that are more of observed than predicted nature. The present study used only last 5 years data for making the proposed model. The study's findings are extremely helpful for making decision making in coastal areas of Odisha, India, regarding the best time to plant wheat. This study also goes further to examine other important crops in the area, such as rice, corn, sugarcane, and others, in order to assess how well they perform under anticipated weather conditions. This information may be used to make crop selection decisions for the upcoming monsoon season.

Using statistical factors from the gathered data, modelling techniques are utilised to forecast production. Except for PE-2018, K-NN efficiency is still slow. Most machine learning algorithms concentrate on the nodular yield of these above-ground signals, which is about 60%. Numerous external factors, such as the shifting environment, have an impact on the remaining 40%. Additionally, both approaches may be used to get reliable findings for big databases.

The suggested technique is a revolutionary weather-based crop selection system that chooses crops for a plot of land based on anticipated weather parameters and the soil's characteristics. The Telangana state's agro-climatic zones' soil and weather factors are used to train the categorization model. Utilizing RNN, seasonal weather forecasts are made. The findings of the comparison between the prediction results and traditional ANN demonstrate improved prediction accuracy. To find more than one crop that will grow well on a piece of land, a random forest classifiers with an extra threshold parameter is utilised. Furthermore, depending on anticipated meteorological factors, the suggested technique also recommends the ideal seeding timing for each crop.

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