International Journal of Advanced Science and Computer Applications (2024); 4(1):
DOI: 10.47679/ijasca.v4i1.59
https://ijasca.org/index.php/ijasca

RESEARCH ARTICLE

Crop yield prediction by Mestrial Environ Netsual Network (MENN)

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Published online: 14 March 2024

Abstract

Crop yield prediction methods can roughly predict actual yield, although better yield prediction performance is still sought. In the existing methodologies the crop yield prediction outcomes are based on the past experience data and failed to predict the exact outcomes of the crop yield. Hence, a hybrid approach namely Crop yield prediction by Mestrial Environ Netsual Network (MENN) has been proposed to overcome the challenges in the existing approaches and to predict the crop yield with impeccable manner. In previous techniques, the change in phenotype as well as genes in the seed and the plant pathology are not combined as a new model. Hence, Mestrial Neural Network (MNN) has been proposed which consist of Task allocation layer, Subset-net layer and Integrated yield estimation layer to predict the sowing seed gene along with the phenotype and pathology. Also, incorporated pathology module examines the phenotype of respected sowing seed selected for the prediction of yield value. Moreover, while combining the statistical data and image data for the prediction, the generalization ability of prediction model was affected by reason of the images that shared the same timestamp as the statistical data were eliminated as part of the procedure for creating the dataset utilized in the existing approaches. Hence, a novel, Yield Environ Netsual Network (YENN) has been proposed which is consists of two deep networks; (i) Deep Q network (DQN) and (ii) VGG16 for the generalization ability as well as the elimination of data caused by the same timestamp is rectified. Here, VGG-16 is utilized for processing the given input images. As a result, the proposed model well examine the potential disease based on the gene and environment conditions and effectively predict the yield value of crops.

Keyword: Crop, Yield prediction, machine learning, sowing seed, phenotype, plant pathology, statistical data, prediction model, agricultural

Introduction

One of the key areas of societal concern is agriculture, because it gives a substantial amount of food. Due to the scarcity or lack of food with an increasing population, several countries still suffer from hunger today. The combined effects of a growing population, erratic weather patterns, soil erosion, and climatic change need methods to guarantee agricultural development and output in a timely and consistent way. It also needs to help increase the sustainability of agricultural food production. These needs suggest that the appraisal of land, the safeguarding of crops, and the forecasting of agricultural yields are more crucial to the global food production [1-3].

Crop yield prediction is one of the difficult topics in precision agriculture, and several models have been suggested and proven thus far. As agricultural production varies on a range of factors, including climate, weather, soil, the usage of fertilizer, and seed type, this challenge necessitates the use of many datasets. This shows that predicting agricultural yields involves a number of challenging processes and is not a simple operation. Nowadays, crop yield prediction models can roughly forecast the actual yield, but a higher yield prediction performance is still desired. Machine learning, a subset of Artificial Intelligence (AI) that focuses on learning, is a useful method that can estimate yields more accurately utilizing a variety of characteristics. Machine learning (ML) can find patterns and correlations and uncover information from datasets. The models must be trained using datasets with representations of the outcomes based on prior knowledge [4-7].

The classic ML approaches work based on feature extraction to forecast crop productivity. Artificial neural networks, fuzzy information networks, decision trees, regression analysis, clustering, principal component analysis, Bayesian belief networks, time series analysis, and Markov chain models are some of the mathematical and statistical techniques used in machine learning (ML) approaches for crop prediction. Due to the availability of numerous data from various sources to uncover hidden information, the use of these machine learning techniques in crop production exhibits even more amazing advantages [8-10]. Yet, when the ML algorithms are trained, it is frequently challenging to locate the best characteristics. Deep Learning (DL) approaches, such as Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) networks, have been created recently and

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have been utilized successfully in several studies as an alternative. Despite the fact that DL approaches have been applied in the field of agricultural production prediction, the majority of research are based on deterministic forecasts, which don't reveal anything about the uncertainty around model projections. Although the probabilistic form of DL algorithms has recently been proposed in certain research, but because of its high complexity and demanding resource needs, it has not gained much momentum in the engineering literature [11-13]. Artificial neural networks (ANNs), a type of biologically inspired computer paradigm, have been widely used in a range of fields because of its performance in generalization and representation. While several approaches, such as structure-constructing methods and parameter-tuning algorithms, have been proposed for ANNs, they still have difficulties with big structure, computing complexity, and sluggish convergence when addressing complicated problems [14,15]. Although there are many techniques proposed for the crop yield prediction but still there is a need to enhance in crop yield prediction on past experience data also need to improve the exact outcomes of the crop yield. Given the aforementioned issues, a unique neural network is necessary to swiftly and effectively resolve complicated issues. The main contribution of this paper is as follows:

- In crop yield prediction, a hybrid approach named as Mestrial Environ Netsual Network (MENN) has been proposed to overcome the challenges in the existing approaches in the prediction of crop yield with impeccable manner.
- To predict the sowing seed gene along with the phenotype and pathology Mestrial Neural Network (MNN) has been proposed which consist of (i) Task allocation layer (ii) Subset-net layer and (iii) Integrated yield estimation layer, it examines phenotype of respected sowing seed and selected for the prediction of summation yield value.
- To process the statistical data and image data for the prediction, Yield Environ Netsual Network (YENN) has been proposed. Which consists of (i) Deep Q network (DQN) and (ii) VGG16. Also, VGG-16 is utilized for the generalization ability as well as the elimination of data caused by the same timestamp is rectified.

Thus, the Crop yield prediction by Mestrial Environ Netsual Network (MENN) predict the crop yield effectively with the phenotype and pathology sowing seed gene and accurately process the statistical data and image data for prediction. The content of the paper is organized as follows: section 2 describes related works, section 3 provides novel solution, the implementation results and its comparison are provided in section 4; finally, section 5 concludes the paper.

Literature Review and Method

Jeong and Yeom [16] suggested a strategy that combines a crop model with a deep learning model for the early prediction of rice production at the pixel level for various agricultural systems in South and North Korea. To begin with, satellite-integrated crop models were used to calculate a reference rice yield at the pixel level. To take use of the benefits of crop models, the deep learning model's target labels were the pixel-scale reference rice yields. By forecasting the most effective model roughly two months before harvest time, models of five alternative deep learning network architectures were used to help decide the hybrid structure of long-short term memory (LSTM) and one-dimensional convolutional neural network (1D-CNN) layers. The human intervention variable according to the agricultural environment can be included to the model.

Gavahi et al [17] proposed DeepYield which is a hybrid structure that combines the ConvLSTM layers with the 3-Dimensional CNN (3DCNN), in order to extract spatiotemporal features more precisely and reliably. The MODIS Land Surface Temperature (LST), Surface Refectance (SR), and Land Cover (LC) data across 1836 key soybean growing counites in the Contiguous United States are used to train the models, together with county-based historical yield data (CONUS). Comparisons are made between the created models' predicting abilities and those of competing strategies such as CNN + GP, CNNLSTM, and Decision Trees. Only SR and LST have been regarded as the main contributing elements in this investigation. Further research will include the addition of additional crucial inputs such hydrological factors, meteorological and environmental data, and plant genotypes that influence plant development.

Alibabaei et al [18] looked at how well the two deep learning models, such as Bidirectional Long Short-Term Memory and Bidirectional Gated Recurrent Units, can forecast end-of-season yields. To calculate end-of-season yield, the models estimate previous data on soil water content, irrigation timing, and climate. At a site in Portugal, this method's use was examined for tomato and potato yields. For the validation dataset, the Bidirectional Long Short-Term Memory fared superior to the Gated Recurrent Units network, the Long Short-Term Memory, and the Bidirectional Gated Recurrent Units network. The model's MSE ranged from 0.017 to 0.039 and was able to forecast yield while accounting for the nonlinear link between soil water content, climatic data, and irrigation volume. One drawback of the BLSTM model was that it required more time to train than previous models that had been used for the prediction of yield.

Mishra et al [19] estimated the impact of climatic variability on the agricultural sector based on the output of rice crops and meteorological characteristics of three coastal regions of Odisha, an Indian state. The proposed prediction model is composed of three phases. In the first phase, two datasets representing three coastal areas are subjected to individual applications of three feature ranking approaches, including Random Forest, Support Vector Regression-Recursive Feature Elimination (SVRRFE), and F-Test, and features are ranked according to their algorithms. The top five best features were determined using the Borda Count fusion technique on the characteristics that were ranked in the first phase. At last, the relevance of the suggested fusion-based ranking prediction model has been assessed and validated using the statistical paired T-test. Yet, in the future, the unrelated or insignificant issues can be eventually addressed by developing optimum tactics.

Feng et al [20] presented evidence for the occurrence of spatial non-stationarity and temporal non-stationarity in winter wheat yield prediction (TWR) based on geographically weighted regression (GWR) and temporally weighted regression. A model for a geographically and temporally weighted neural network (GTWNN) was put forth by combining a geographically and temporally weighted regression (GTWR) with an artificial neural network (ANN) and publicly accessible data sources, such as satellite imagery and temperature data. In order to produce out-of-sample predictions for a more reliable assessment, the leave-one-year-out technique was used, resulting in a total of 12 test years from 2008 to 2019. According to the experiment's findings, the suggested GTWNN outperformed ANN, GTWR, and support vector regression (SVR). A sensitivity study was not conducted to identify the period that will best balance the preservation of vegetation growth features with the increase in data dimensions.

Paudel et al [21] presented a crop yield forecasting strategy for several geographical levels, based on regional agricultural yield projections from machine learning. With its data-driven methodology, machine learning is able to use bigger data sets and identify nonlinear correlations between predictors and output at the regional level. A general machine learning pipeline was created by the author to illustrate the advantages of regional agricultural yield predictions in Europe. Also, estimated crop yields for 35 case studies, covering nine nations that are significant producers of six crops, in order to assess the accuracy and utility of regional predictions (soft wheat, spring barley, sunflower, grain maize, sugar beets and potatoes). For an ordinary harvest, these estimates were quite accurate, but less so for exceptional harvests.

Alexandros Oikonomidis et al [22] presented the cutting-edge use of deep learning for crop production prediction is intended. Using a systematic review of the literature (SLR). Also, examine the most pertinent papers and found 456 pertinent studies, and after applying selection and quality assessment criteria to the pertinent studies, we chose 44 primary studies for additional analysis. Regarding the main motives, the target crops, the algorithms employed, the features used, and the data sources used, a detailed review and synthesis of the primary studies was conducted. We found that the most popular technique, the convolutional neural network (CNN), performs best in terms of root mean square error (RMSE). However, need to build on the outcomes of this SLR study.

K. Vignesh et al [23] presented Deep learning-based algorithms are used to extract beneficial crops for forecasting. A comprehensive crop yield prediction system that is able to link raw data to expected crop yields is produced by combining data mining and deep learning. The proposed study makes use of a Visual Geometry Group and Discrete Deep Belief Network. To estimate agricultural production, the (VGG) Net classification method is preferred above the modified chick swarm optimisation method. The data parameters were provided to the Network's stacked layers one after another. The network architecture is used to build a crop production forecast environment based on the input parameters. The best features of the input data are preprocessed using the tweak chick swarm optimisation technique, and the best output is used as input for the classification procedure. However, need to evaluate the effectiveness of the implemented strategy.

Maninder Singh Dhillon et al [24] studied the Free State of Bavaria (70,550 km2), Germany, is the subject of a project that explores the coupling of crop modelling and machine learning (ML) to enhance the yield forecast of winter wheat (WW) and oil seed rape (OSR). The major goals are to determine whether a coupling strategy [Light include Efficiency (LUE) + Random Forest (RF)] will produce better and more accurate yield forecasts in comparison to those obtained from other models that do not include the LUE. To find the most accurate crop monitoring predictors, four different RF models [RF1 (input: Normalised Difference Vegetation Index (NDVI)), RF2 (input: climate variables), RF3 (input: NDVI + climate variables), and RF4 (input: LUE generated biomass + climate variables)] and one semi-empiric LUE model were designed with various input requirements. However, there is a need to increase the yield accuracy with the influential variables of the crop and phenology-related inputs (LUE biomass), extra-terrestrial radiation, solar radiation, evapotranspiration, extra-terrestrial radiation, soil moisture, snow cover (for OSR) and temperature.

Shuaipeng Fei et al [25] assessed the yield prediction capabilities of a low-cost multi-sensor (RGB, multi-spectral, and thermal infrared) UAV platform, a set of thirty wheat cultivars and breeding lines were cultivated under three irrigation treatments, i.e., light, moderate, and high irrigation treatments. In each ML model, multi-sensor data fusion-based yield prediction demonstrated more accuracy than individual-sensor data. Across the multi-sensor data, the predictions of ensemble learning demonstrated strong R2 values up to 0.692, which was higher than that of individual ML models. Calculations were made for the ratio of prediction performance to inter-quartile range (RPIQ), residual prediction deviation (RPD), and root mean square error (RMSE). However, need to improve in plant breeding.

Form the analysis it is determined that [16] the human intervention variable was excluded and [17] does not focus on the phenotype and hydrological factors. The time required to train the proposed model is high in [18] and [19] requires optimum tactics for addressing the insignificant issues. A sensitivity study was not conducted in [20] to choose the time period that would best combine the retention of vegetation growth traits and the proposed model in [21] is not suitable for exceptional harvests. Hence to tackle the aforementioned issues, a novel solution has to be proposed. [22] need to build on the outcomes of this SLR study. [23] need to evaluate the effectiveness of the implemented strategy. [24] need to consider increasing the yield accuracy with the influential variables. [25] need to improve in plant breeding.

Overall, from these studies, it is understood that there is need to improve the prediction in crop yield and also need to evaluate the effectiveness in the implementation to get the accurate output. Moreover, need to consider the phenotype and hydrological factors. Hence, to achieve the aforesaid requirements a novel efficient, and reliable method is proposed for successful prediction of crop yield.

Crop yield prediction by Mestrial Environ Netsual Network (MENN)

It is crucial for decision-makers at the national and regional levels to anticipate crop yields for quick decision-making. Farmers choose what to produce and when to grow it with the aid of an accurate crop production prediction model. There are several methods for predicting agricultural yields. In the existing methodologies the crop yield prediction outcomes are based on the past experience data. To overcome the challenges in the existing approaches a hybrid approach is required to predict the crop yield with impeccable manner, so an innovative approach namely **Mestrial Environ Netsual Network (MENN)** has been proposed. Furthermore, while a new factor or an issue arises the designed ML models are failed to predict the exact outcomes of the crop yield. This is because the change in phenotype as well as genes in the seed and the plant pathology are not combined as a new model in the existing approaches. Hence a Mestrial Neural Network (MNN) has been proposed in which it is consist of (i) Task allocation layer (ii) Subset-net layer and (iii) Integrated yield estimation layer to predict the sowing seed gene along with the phenotype and pathology. Then the shaping eco-system module for the factors which influencing the yield value. Following that, the pathology module will examine the potential diseases based on the gene and environment conditions. After the completion of all processes, using the Integrated yield estimation layer the average weight of each sowing seed in one plant is estimated in order to predict the summation yield value. While combining the statistical data and image data for the prediction, the generalization ability of prediction model was affected since the images that shared the same timestamp as the statistical data were eliminated as part of the procedure for creating the dataset utilized in the existing approaches. This is because of the combination of both the multi-class and binary probability estimates from the image-based and statistical-based models. Hence, Yield Environ Netsual Network (YENN). It consists of two deep networks; (i) Deep Q network (DQN) and (ii) VGG16. The generalization ability as well as the elimination of data caused by the same timestamp is rectified by, modifying the DQN agent in the DQN network is, constructed by sequentially stacking the MNN layers, initialising the parameters using the weights saved during the MNN training process, and adding the MNN and VGG 16 output mapping layer to map the MNN and VGG 16 output to Q-values. Where the VGG-16 is utilized for processing the given input images. Due to the dual combination, the yield prediction environment is formed in order to predict the yield value of crops. As a result, a unique machine learning approach for agricultural yield prediction is advocated.

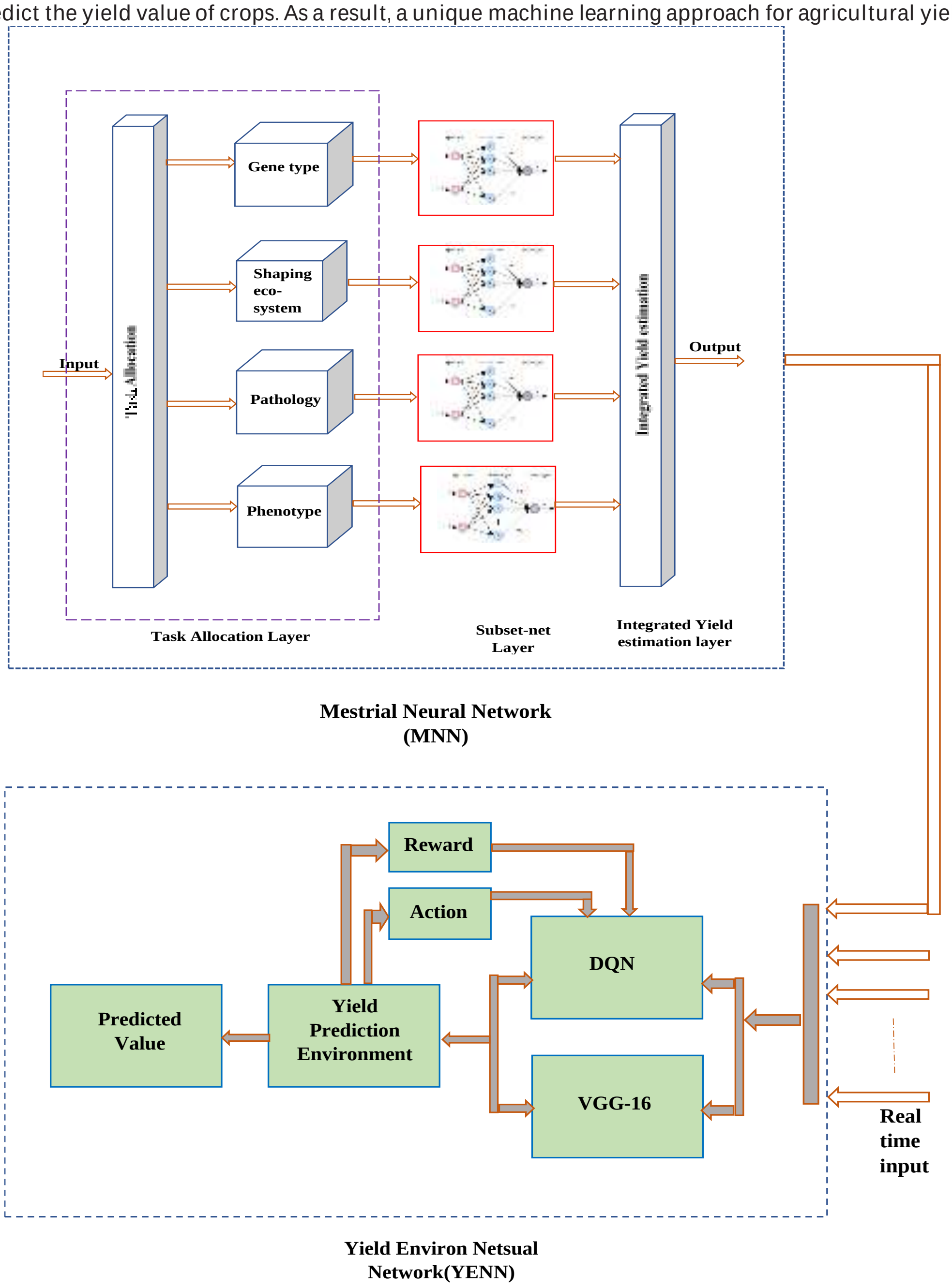

Fig 1. Architecture of Mestrial Environ Netsual Network (MENN)

Figure 1 represents the architecture diagram of the Mestrial Environ Netsual Network (MENN). The first phase is Mestrial Neural Network (MNN) which consist of three layers, they are (i) Task allocation layer (ii) Subset-net layer and (iii) Integrated yield estimation layer. It creates the gene, respected Biotic and Abiotic factors with the shaping ecosystem module examine the potential diseases based on the gene and environment conditions and selected for the prediction of yield value. Then the second phase, a novel, Yield Environ Netsual Network (YENN) which consists of two deep networks; (i) Deep Q network (DQN) and (ii) VGG16. It initializes the parameters using the weights saved during the MNN training process, and adding the MNN and VGG 16 output mapping layer to map the MNN and VGG 16 output to Q-values and process the input images and predict the yield value of crops.

Mestrial Environ Netsual Network (MENN)

An innovative approach namely Mestrial Environ Netsual Network (MENN) has been proposed. In this proposed methodology the sowing seed gene along with the phenotype and pathology is predicted by the Mestrial Neural Network (MNN) which consist of (i) Task allocation layer (ii) Subset-net layer and (iii) Integrated yield estimation layer. To predict the crop yield with impeccable manner the Mestrial Neural Network is follow as shown in equation (1):

$$\theta^*(m) = \underset{u \in U}{\arg max} \; \alpha \sum_{m' \in M} Q\,(m',u).F^*\,(m',u).G^*\,(m',u) \qquad (1)$$

Where, $\theta^*(m)$ is the mestrial environ netsual network, (m,u) is the value function it is defined for each state-action pair is an estimate of the expected crop yield, $\underset{u \in U}{\arg max}$ is maximize by determining the sample observation, θ is to calculate the angle, $Q\,(m',u)$ is the first layer of mestrial environ netsual network named as task allocation layer; $F^*\,(m',u)$ is the second layer of the mestrial environ netsual network named as subset-net layer; $G^*\,(m',u)$ is the third layer of the mestrial environ netsual network integrated yield estimation layer. For task allocation layer as shown in equation (2):

$$\hat{Q}_{(m',u)}\gamma_0 = \sum_{a \in K} E_{x,y'}\gamma_y + \sum_{u \in U} n_u D_{x,u} \qquad (2)$$

Where, k is the set of explanatory variables, U is the set of interactions, $\hat{Q}$ is predicted crop yield of sample x, γ_0 is the intercept of crop yield, γ_y is the additive effect of variable y, $E_{x,y}$ is the explanatory variable y of sample x, n_u is the effect of interaction u, and $D_{x,u}$ is the interaction variable x of sample u.

Using the Task allocation layer each task is subdivided in the neural networks, then the corresponding divided layer will be activated based on the logical conditioning to perform the operation in the subset-net layer as shown in equation (3):

$$\hat{F}_{(m',u)} = \sum_{b \in B} \varphi_{u,b} \; B_b(E_x) \qquad (3)$$

Where, b is the relationships between explanatory variables and crop yield, $\varphi_{u,l}$ is the sowing seed input, E_x is the binary variable indicating whether interaction x is best.

At first using the given sowing seed input the gene creation operation is performed by the subset-net layer. After the gene creation the respected Biotic and Abiotic factors is considered in the shaping eco-system module for the factors which influencing the yield value. Following that, the pathology module examine the potential diseases based on the gene and environment conditions. Then the phenotype of respected sowing seed is selected for the prediction of yield value. For integrated yield estimation layer as shown in equation (4):

$$\hat{G}_{(m',u)} = \sum_{u \in U} \left(\frac{((N_i - \bar{N}) * (P_i - \bar{P}))}{(\sigma_N - \sigma_P)} \right) \qquad (4)$$

Where, N and P are measured and predicted values, $\bar{N}$ is the number of the observation in integrated yield estimation, $\bar{P}$ is the value of observation in the integrated field, $\sigma_N - \sigma_P$ is the summation yield value.

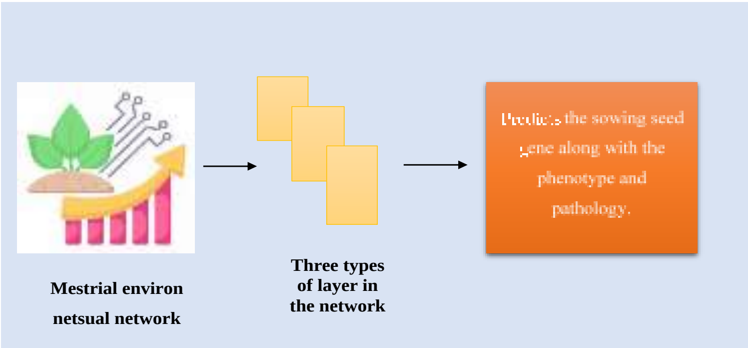

Fig 2. Architecture diagram of the mestrial environ netsual network

Figure 2 represents the architecture diagram of the mestrial environ netsual network it consist of three layers of network, task allocation layer, subset-net layer, integrated yield estimation layer. It predicts the sowing seed gene along with the phenotype and pathology.

After the completion of all processes, using the Integrated yield estimation layer the average weight of each sowing seed in one plant is estimated in order to predict the summation yield value. For that, a straive function is added to the integrated yield estimation layer to differentiate between common, particular, and critical factors in order to estimate the value by competing them against one another also predict crop yield based on farm conditions, social factors and climatic inputs and the function is applied to the result of the output layer which gives the predicted value and provides promising results in a shorter time with more accuracy. Followed by the Mestrial Neural Network the statistical data along with image and estimated data is combined for the precise prediction of crop yield which is explained in the next subsection.

Yield Environ Netsual Network (YENN)

Yield Environ Netsual Network (YENN) consists of two deep networks; (i) Deep Q network (DQN) and (ii) VGG16. The statistical data along with image and estimated data is combined for the precise prediction of crop yield by the utilization of yield environ netsual network as shown in equation (5):

$$Y = \sum_{e=1}^{n} w_e j_e \qquad (5)$$

Where, y is the yield environ netsual network, n is the number of input units to the neuron, w is the weight of e^{th}, j is the e^{th} input value to neuron. Then the Deep Q network (DQN) has progressed has massive data growth and enhanced measure persistence to create new chances for agricultural frameworks to decide, assess, and acknowledge extensive data processes and extract significant crop features for prediction and to forecast the crop yield, constructed by sequentially stacking the MNN layers, initialising the parameters using the weights saved during the MNN training process. Weight normalization on the MNN layer's weights can be conducted during the DQN network training procedure to assist speed up the convergence of the related weights training algorithms. Furthermore, a fraction of the weights of the MNN layers can be pulled out during training to improve generalization performance. For DQN layer as shown in the equation (6):

$$C_t^{r,s} = f\,(h_1\, C_{t-c}^{r,s-1} + h_2 C_t^{r,s-1} + j \qquad (6)$$

Where, f represents the activation function, h_1, h_2 represents the weight, j represents as bias value, t is the output in r^{th} layer and s^{th} block which is denoted as $C_t^{r,s}$.

Then the VGG16 is an input image without preprocessing was randomly divided into the training, validation, and testing dataset. After giving the input images it is pre-processed by the utilization of VGG 16 as shown in equation (7):

$$m_{(x,y)} = f_\pi(h_x, h_y - h_x) \quad (7)$$

Where, h_x denote dimensional features on points, f_π computes the inner product of the learnable parameters. h_x, h_y is the yields descriptive geometric features of input images, which can be directly used to compute candidate data costs for preprocessing.

The generalization ability as well as the elimination of data caused by the same timestamp is rectified by, modifying the DQN agent in the DQN network is, constructed by sequentially stacking the MNN layers, initialising the parameters using the weights saved during the MNN training process, and adding the MNN and VGG 16 output mapping layer to map the MNN and VGG 16 output to Q-values. Where the VGG-16 is utilized for processing the given input images. Due to the dual combination, the yield prediction environment is formed in order to predict the yield value of crops.

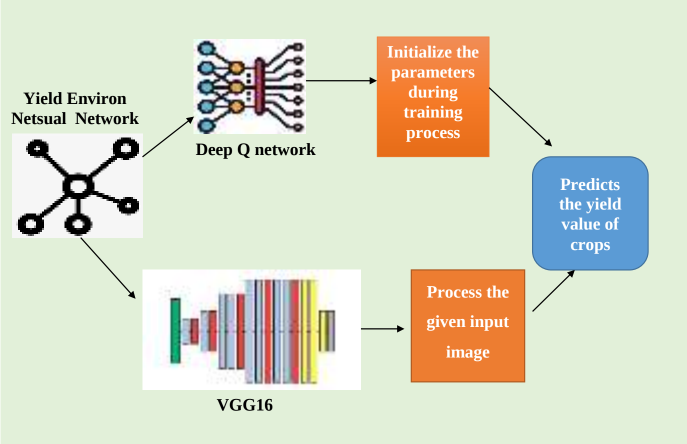

Fig 3. Architectural DIAGRAM OF Yield environ netsual network

Figure 3 represents the architectural diagram of the yield environ netsual network it consists of Deep Q network and VGG16. In Deep Q network it initializes the parameters during the training process and VGG16 utilizes for processing the given input image. The dual combination of the yield prediction environment is formed in order to predict the yield value of crops.

Overall, the proposed model Mestrial Environ Netsual Network (MENN) predict the sowing seed gene along with the phenotype and pathology and examine the potential diseases based on the gene and environment conditions and selected for the prediction of yield value then Yield Environ Netsual Network (YENN consists of two deep networks; (i) Deep Q network (DQN) and (ii) VGG16, it initialize the parameters using the weights saved during the MNN training process, and adding the MNN and VGG 16 output mapping layer to map the MNN and effectively process the given input images and predict the yield value of crops..

Results and Discussion

This section includes a thorough discussion of the implementation results, as well as the performance of the proposed system and a comparison section to ensure that the proposed system is applicable for crop yield prediction by mestrial environ netsual network (MENN).

System configuration

The proposed system is simulated in python and this section provides a detailed description of the implementation results and the performance of the proposed system and a comparison section to ensure that the proposed system performs valuable.

This work has been implemented in the working platform of python with the following system specification and the simulation results are discussed below.

OS : Windows 10 (64-bit)
Software : Python
RAM : 8 GB RAM
Processor : Intel i5

Simulated output of the proposed model:

The simulated output of the proposed model for Crop yield prediction by Mestrial Environ Netsual Network (MENN) has been explained in this section.

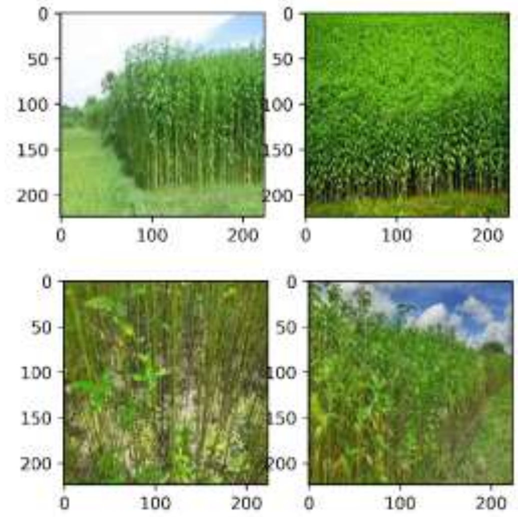

Fig 4. Output of the crop yield prediction from image data

Figure 4 represents the output of the crop yield prediction from image data, Early detection and control of agricultural yield prediction can aid in increasing productivity and profit, as well as achieving maximum crop output at the lowest cost. The output of the crop yield prediction is well efficient because of the novel technique used in the mestrial neural network, it will examine the potential diseases based on the gene and environment conditions. Then the phenotype of respected sowing seed is selected for the prediction of yield value.

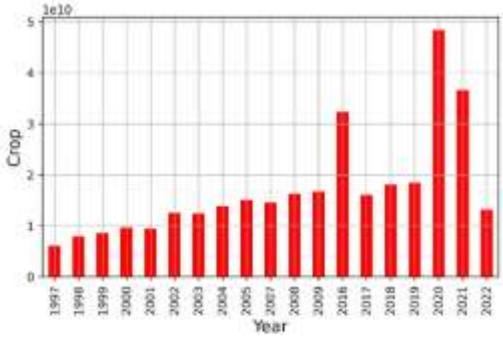

Fig 5. Crop yield production based on year

Figure 5 represents the crop yield production based on the year, in 1997 it achieves 0.5, in 1998 it achieves 0.7, in 1999 it achieves 0.8, in 2000 it achieves 0.98, in 2001 it achieves 1.2, in 2003 it achieves 1.7, in 2004 it achieves 1.3, in 2005 it achieves 1.4, in 2007 it achieves 1.3, in 2008 it achieves 1.5, in 2009 it achieves 1.55, in 2016 it achieves 3.2, in 2017 it achieves 1.6, in 2018 it achieves 1.8, in 2019 it achieves 1.9, in 2020 it achieves 4.8, in 2021 it achieves 3.68, in 2022 it achieves 1.3. From the year 1997 to 2022 the maximum value attains 4.8 in 2020 and minimum value attains 0.7 in 1997. Based on the year from 1997 to 2022 it is well efficient because of the novel technique using the Integrated yield estimation layer the average weight of each sowing seed in one plant is estimated in order to predict the summation yield value.

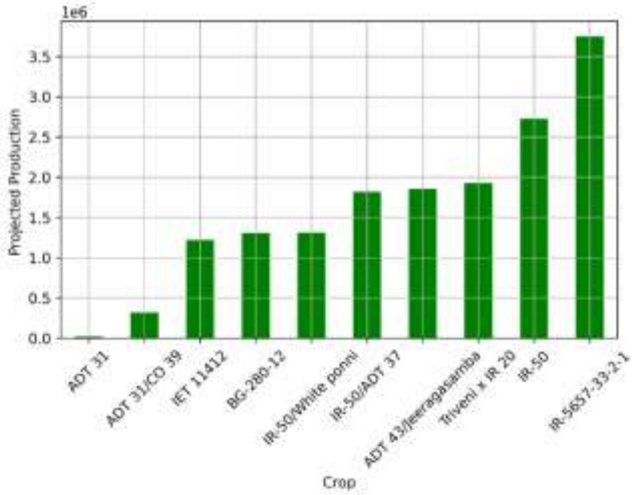

Fig 6. Output of the projected production result

Figure 6 illustrates the projected production result with various crop, ADT-31 achieves 0.07, ADT 31/CO 39 achieves 0.35, IET 11412 achieves 1.3, BG-280-12 achieves 1.35, IR-50/White ponni achieves 1.35, IR-50/ADT 37 achieves 1.7, ADT 43/ Jeeragasamba achieves 1.75, Triveni × IR 20 achieves 1.9, IR-50 achieves 2.65, IR-5657-33-2-1 achieves 3.8. the output of the projected production result is improved because of the novel technique used in the proposed system named as Yield Environ Netsual Network is utilized for processing the given input images. Due to the dual combination, the yield prediction environment is formed in order to predict the yield value of crops.

Performance metrics of the proposed model:

In this section, a detailed explanation of the effectiveness of the suggested technique and the result is provided.

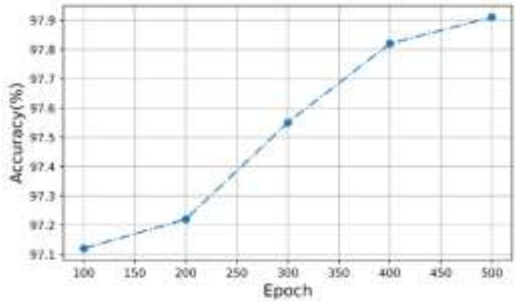

Fig 7. Accuracy of the proposed model

The accuracy of the proposed system for varying the number of input samples has been shown in figure 7. The accuracy of the proposed model achieves the maximum values 97.9% when the number of epoch is increased, and attains the minimum value of 97.11%. The accuracy of the proposed system has been increased by using Deep Q Network which is, constructed by sequentially stacking the MNN layers and initialising the parameters using the weights saved during the MNN training process, and adding the MNN.

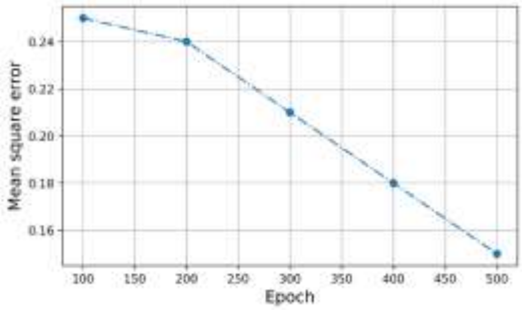

Fig 8. Mean square error of the proposed system

The Mean square error of the proposed system for varying the number of input samples has been shown in figure 8. The mean square error attains the maximum value of 0.27 when the number of epoch is decreased and attains the minimum value of 0.147 when the number of epoch is increased. The mean square error of the proposed system is decreased due to the novel technique Mestrial Environ Netsual Network (MENN) that examine the potential diseases based on the gene and environment conditions. Then the phenotype of respected sowing seed is selected for the prediction of yield value.

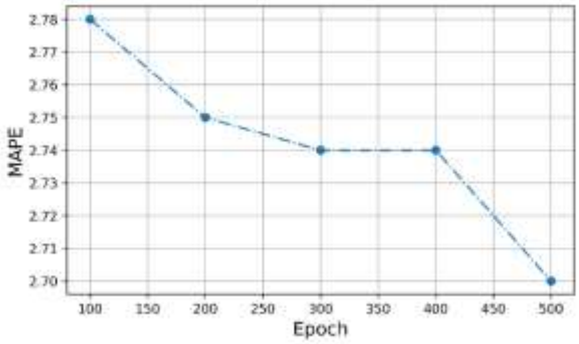

Fig 9. Mean absolute percentage error of the proposed system

The Mean absolute percentage error of the proposed system for varying the number of input samples has been shown in figure 9. The mean absolute percentage error attains the maximum value of 2.78 when the number of epoch is decreased and attains the minimum value of 2.70 when the number of epoch is increased. The mean absolute percentage error of the proposed system is decreased due to the utilization of Integrated yield estimation layer the average weight of each sowing seed in one plant is estimated in order to predict the summation yield value.

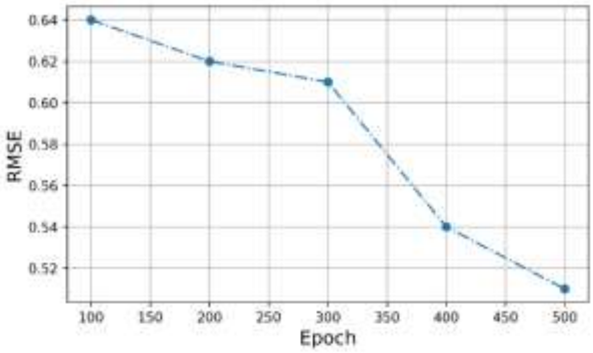

Fig 10. Root mean square error of the proposed system

The Root mean square error of the proposed system for varying the number of input samples has been shown in figure 8. The Root mean square error attains the maximum value of 0.64 when the number of epoch is decreased and attains the minimum value of 0.517 when the number of epoch is increased. The Root mean square error of the proposed system is decreased due to the novel technique Deep Q network, it initialise the parameters using the weights saved during the MNN training process, and adding the MNN and VGG 16 output mapping layer to map the MNN and VGG 16 output to Q-values.

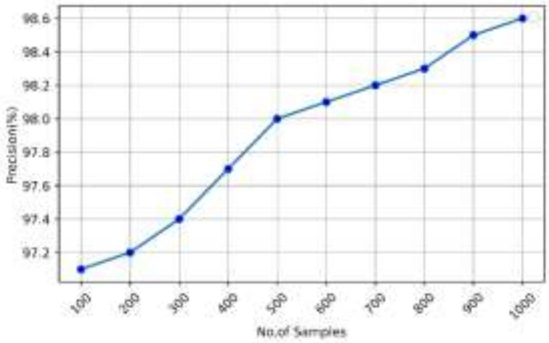

Fig 11. Precision of the proposed system

The precision of the proposed system for varying the number of samples has been shown in figure 11. The precision of the proposed system achieves a maximum value of 98.6% when the number of samples is increased to 1000 and attains a minimum value of 97.1% when the number of samples is reduced to 100. The precision of the proposed system has been increased by the utilization of the Task allocation layer each task is subdivided into the neural networks, then the corresponding divided layer will be activated based on the logical conditioning to perform the operation in the subset-net layer.

Comparison of the proposed model

This section emphasizes the effectiveness of the proposed model by comparing it with the outcomes of existing methodologies and illustrating their outcomes based on several metrics. The comparisons are made from the previous techniques with the various Precision, MAE (Mean absolute error), RMSE (Root mean square error), R value, accuracy. Comparisons are made with the existing techniques such as MLR (multiple linear regression), ANN (Artificial neural network), SVR (support vector regression), KNN (K-Nearest Neighbour), RF (Random forest), MLR-ANN, NB (Naïve Bayes) [26,27].

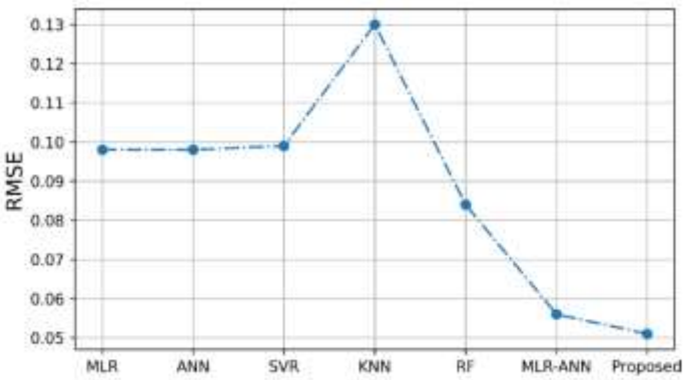

Fig 12. Comparison of the Root mean square error

Figure 12 represents the comparison of the root mean square error with existing techniques such as MLR, ANN, SVR, KNN, RF, MLR-ANN. When compared with existing technique such as MLR, ANN, SVR, KNN, RF, MLR-ANN it attains 0.098, 0.098, 0.099, 0.13, 0.083, 0.057. When compared to existing techniques proposed system achieves 0.05. The proposed attains low root mean square error because of the technique used in the proposed system named as Mestrial Neural Network (MNN).

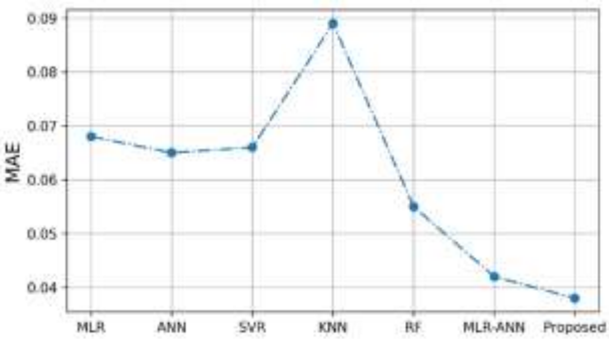

Fig 13. Comparison of the Mean absolute error

Figure 13 represents the comparison of the mean absolute error with existing techniques such as MLR, ANN, SVR, KNN, RF, MLR-ANN. When compared with existing technique such as MLR, ANN, SVR, KNN, RF, MLR-ANN it attains 0.068, 0.065, 0.066, 0.09,0.055, 0.043. When compared to existing techniques proposed system achieves 0.038. The proposed attains low mean absolute error because of the technique used in the proposed system named as Mestrial Neural Network (MNN).

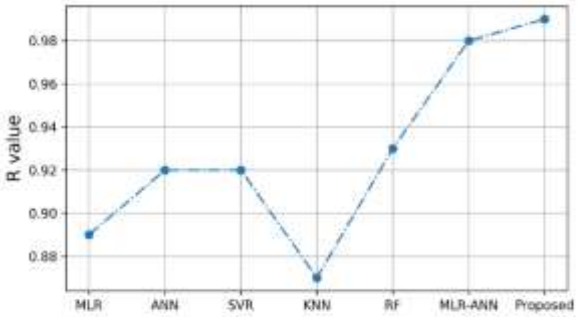

Fig 14. Comparison of the R value

Figure 14 represents the comparison of the R value with existing techniques such as MLR, ANN, SVR, KNN, RF, MLR-ANN. When compared with existing technique such as MLR, ANN, SVR, KNN, RF, MLR-ANN it attains 0.89, 0.92, 0.92, 0.865, 0.93, 0.97. When compared to existing techniques proposed system achieves 0.987. The proposed attains high R value because of the technique used in the proposed system named as Yield Environ Netsual Network (YENN).

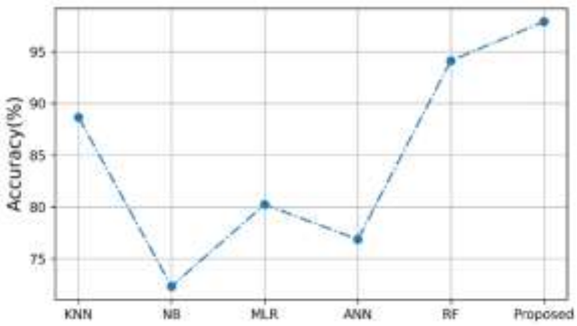

Fig 15. Comparison of the Accuracy

Figure 15 represents the comparison of the accuracy with existing techniques such as KNN, NB, MLR, ANN, RF. When compared with existing technique such as KNN, NB, MLR, ANN, RF it attains 88, 72, 80, 77, 94. When compared to existing techniques proposed system achieves 99. The proposed attains high accuracy because of the technique used in the proposed system named as Yield Environ Netsual Network (YENN).

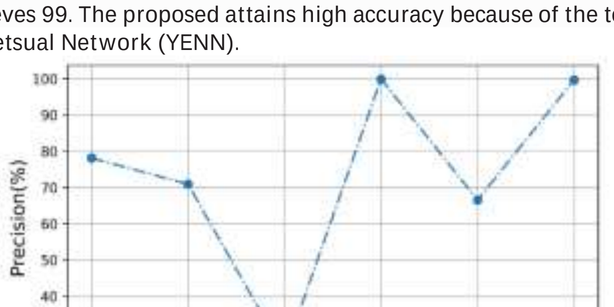

Fig 16. Comparison of the precision

Figure 16 represents the comparison of the accuracy with existing techniques such as KNN, NB, MLR, ANN, RF. When compared with existing technique such as KNN, NB, MLR, ANN, RF it attains 79, 71, 23, 99.9, 68. When compared to existing techniques proposed system achieves 100% of precision. The proposed attains high precision because of the technique used in the proposed system named as Deep Q network (DQN).

Overall the proposed system achieves low root mean square error of 0.05%, low mean absolute error of 0.38, high R value of 0.987, high accuracy of 99%, high precision of 100% when compared to the existing techniques such as MLR (multiple linear regression), ANN (Artificial neural network), SVR (support vector regression), KNN (K-Nearest Neighbour), RF (Random forest), MLR-ANN, NB (Naïve Bayes).

Conclusions and Recommendations

An innovative approach namely Mestrial Environ Netsual Network (MENN) has been proposed. In this proposed methodology the sowing seed gene along with the phenotype and pathology is predicted by the Mestrial Neural Network (MNN) which consist of Task allocation layer each task is subdivided into the neural networks, then the corresponding divided layer is activated based on the logical conditioning to perform the operation in the subset-net layer. A straive function is added to the integrated yield estimation layer to differentiate between common, particular, and critical factors in order to estimate the value by competing them against one another. The DQN network initialize the parameters using the weights saved during the MNN training process and VGG16 is utilized for processing the given input images. The output of the proposed system attains accuracy of 97.9%, mean square error of 0.27%, mean absolute percentage error of 2.70, root mean square error of 0.517. Overall the proposed system achieves low root mean square error of 0.05%, low mean absolute error of 0.38, high R value of 0.987, high accuracy of 99%, high precision of 100% when compared to the existing techniques such as MLR (multiple linear regression), ANN (Artificial neural network), SVR (support vector regression), KNN (K-Nearest Neighbour), RF (Random forest), MLR-ANN, NB (Naïve Bayes).

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